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Artificial Intelligence for Trusted Autonomous Satellite Operations

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ABSTRACT

Recent advances in Artificial Intelligence (AI) and Cyber-Physical Systems (CPS) for aerospace applications have brought about new opportunities for the fast-growing satellite industry. The progressive introduction of connected satellite systems and associated mission concepts is stimulating the development of intelligent CPS (iCPS) architectures, which can support high levels of flexibility and resilience in an increasingly congested near-Earth space environment. The need for higher levels of automation and autonomy in satellite operations has stimulated numerous research initiatives in recent years, focusing on the progressive enhancement of systemic performance (e.g., addressing safety, integrity and cyber-physical security metrics) and associated monitoring/augmentation approaches that can support Trusted Autonomous Satellite Operations (TASO). Despite these advances, in most contemporary satellite platforms, autonomy is restricted to a specific set of rules and cases, while the transition to TASO requires a paradigm shift in the design of both space vehicles and ground-based systems. In particular, the use of AI is seen as an essential enabler for TASO as it enhances system performance/adaptability and supports both predictive and reactive integrity augmentation capabilities, especially in Distributed Satellite Systems (DSS). This article provides a critical review of AI for satellite operations, with a special focus on current and likely future DSS architectures for communication, navigation and remote sensing missions. The aim is to identify key contemporary challenges and opportunities associated with space iCPS design methodologies to enhance the performance and resilience of satellite systems, supporting the progressive transition to TASO. A comprehensive review of relevant AI techniques is presented to critically assess the potential benefits and challenges of each method for different space applications. After describing the specificities of DSS and the opportunities offered by iCPS architectures, the co-evolution of space and control (ground and on-board) segments is highlighted as an essential next step towards enabling TASO. As an integral part of this evolutionary approach, the most important legal and regulatory challenges associated with the adoption of AI in TASO are also discussed.

1. Introduction

Satellite systems provide a wide variety of services, which can be easily accessed from almost any location on the globe. These systems have rapidly evolved over the last few decades and have become essential in various application domains, such as communications, navigation, Earth Observation (EO) and astronomy [1]. However, certain aspects of satellite technology, such as trusted autonomous operations, remain to be explored due to the increasing complexity of hardware/software components and associated safety, integrity and cyber-physical security concerns [2]. Present day autonomous systems are capable of executing intelligent functions (e.g., decisions and/or actions traditionally performed by humans) using various computer-based algorithms, often referred to Artificial Intelligence (AI). This requires the ability to gather real-time data from the external operational environment (i.e., sensing), to perform inference and/or

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decision-making functions and to execute proper actions if and when required. Despite the significant progress made in hardware and software technologies, Trusted Autonomous Satellite Operations (TASO) are still largely a research topic and significant investments are needed to fully exploit the anticipated safety, efficiency and sustainability benefits that such operations would bring, possibly leading to the progressive removal of present-day socio-political barriers such as AI ethics, liability and public trust [3]. In many applications, fully autonomous satellite operations are either impractical or undesirable, mainly because a minor error can result in the loss of millions of dollars and, in some cases, lead to human casualties (point-to-point suborbital space transport, Earth-orbiting inhabited space stations, etc.). Therefore, an acceptable level of trust is required for near-Earth operations, especially considering the steady increase of Resident Space Objects (RSO) in Low-Earth Orbits (LEO) and Geostationary Orbits (GEO) [4,5]. Furthermore, to facilitate further progress in TASO research, it is essential to address the implications of trusted autonomy and AI in the evolution of Cyber-Physical Systems (CPS) for space applications, including the co-evolution of system-level requirements (i.e., communication, control and computing) and human-autonomy interactions. Current research trends in this area show that Cyber-Physical-Human (CPH) architectures are evolving with the widespread adoption of Machine Learning (ML) and hybrid AI techniques (e.g., neuro-fuzzy inference engines) and becoming progressively more capable of modulating both the levels of autonomation and the human command/control functions towards achieving specific goals. In this context, we are participating to an evolutionary process where human operators are progressively transitioning to a high-level supervisory role [6].

Over the last few years, Distributed Satellite Systems (DSS) have been at the forefront of this transformation and it is now clear that the use of AI in DSS will play a significant role in easing the transition to TASO. To meet the requirements of future trusted autonomous space vehicles and intelligent operation in highly integrated and information-rich environments, a radical departure from conventional system design and development approaches is required. Going forward, explainability and certification of AI based systems will be critical, particularly in outer space operations where there is a need to simultaneously address safety, security and legal requirements (e.g., liability for the damages these systems may cause). As a result, there is a need to understand the associated technical, ethical and legal challenges that come with these evolving systems.

This article starts with a high-level classification of spaceflight systems (section 1), with a focus on the various categories of Earth orbiting satellites. Then, it moves on to discuss and compare monolithic and distributed satellite configurations (section 2). After that, section 3 focuses on spacecraft autonomous operations, providing an overview of the most promising concepts applied to human and machine collaboration in space operations. Section 4 provides a critical examination of the many AI techniques proposed for space system applications and section 5 discusses how these techniques can be applied in practice to various DSS architectures. The required evolution of spaceflight systems infrastructure is discussed in section 5, which highlights the most promising applications of AI in the different system segments and the need for a co-evolution of DSS space and ground segments. Section 6 discusses current and likely future applications of AI in near-Earth space missions and section 7 addresses safety and security aspects associated to the adoption of AI in DSS. Section 8 concludes the critical review highlighting the open technological, ethical and legal challenges, as well as the ongoing efforts to overcome these challenges and to facilitate the uptake of AI technology in next-generation satellite systems.

2. Spaceflight systems

Thousands of active satellites are currently orbiting Earth and, in recent years [7], there has been an exponential growth of RSO [8], especially in the LEO environment [9]. Each satellite's size, orbital parameters and configuration depend on its intended purpose. The classification of spaceflight systems adopted in this article is presented in Fig. 1. Broadly, spaceflight systems can be grouped into three categories: (1) Space exploration systems [5]; (2) Earth orbital/sub-orbital transport system [10]; (3) Earth orbit satellite systems. Earth-orbiting satellite systems can be further divided into the following categories: (i) Monolithic satellite systems, (ii) Distributed Satellite Systems (DSS) which are discussed broadly in the following sections.

2.1. *Monolithic Satellite Systems*

If a satellite system with its modules or subsystems is physically independent from other space assets, it is classified as a monolithic satellite system. Monolithic systems are still a large fraction of spacecraft being deployed in missions such as deep space exploration, technology demonstration, universities and research centres [11,12]. The need for self-contained hardware and the required redundancy increases the system's overall weight and volume, making it more expensive. A typical monolithic satellite system has the following modules PR: Processor, PL: Payload, DL: Downlink, CM: Communications Module, BUS, which integrates all the modules as depicted in Fig. 2. Monolithic satellite systems are comprehensively reviewed in Refs. [13,14].

2.2. *Distributed Satellite Systems*

DSS consist of multiple spacecraft working together to achieve one or more common objectives. DSS therefore adopt a satellite architecture in which the functional capabilities are shared among many space assets that communicate via wireless networks [15]. The DSS concept is gradually migrating the physical connectivity of various components in conventional satellite systems into wireless connections using either radiofrequency or optical communication methods, i.e., Inter Satellite Links (ISL). Therefore, DSS mission architectures shift away from monolithic systems towards multiple spacecraft/modules of elements that communicate, interact and cooperate with one another [16]. In addition to these new system-wide properties, subdividing the modules over many launches reduces risk, ensuring that the core system is not lost when a launch fails. This approach also offers the flexibility to progressively deploy the system in orbit, thereby allowing the addition of different DSS elements at successive stages. A study by the Research and Development (RAND) corporation showed that distributed systems have the potential to [12]:

1. Weigh less and be less expensive to launch.
2. Perform better during deployment and before the full DSS is completely operational.
3. Show better tolerance to single and multiple failures, with no or graceful degradation of performance.
4. Be more survivable in the event of both cyber and physical attacks.

Due to these distinctive advantages, DSS can deliver a more responsive and resilient solution to meet the expanding demands of the scientific community and also the defence sector, for instance by improving the quality/quantity of measurements and associated data analytics in EO [17], Space-Based Space Surveillance (SBSS) tasks [18–21] and Interplanetary mission [22]. Some notable examples include PRISMA [23], GRACE [24], TerraSAR-X and TanDEM-X missions [25].

2.2.1. *Modularity*

A distinctive attribute of DSS is modularity, Within the broader scope of systems engineering, modularity is a feature of systems that quantifies the degree to which a system's functionalities can be subdivided into distinct modules or clusters which interact with each other [26,27]. Damage to one module can cascade to subsequent modules in a highly interconnected system with minimal modularity, enhancing the risk of a

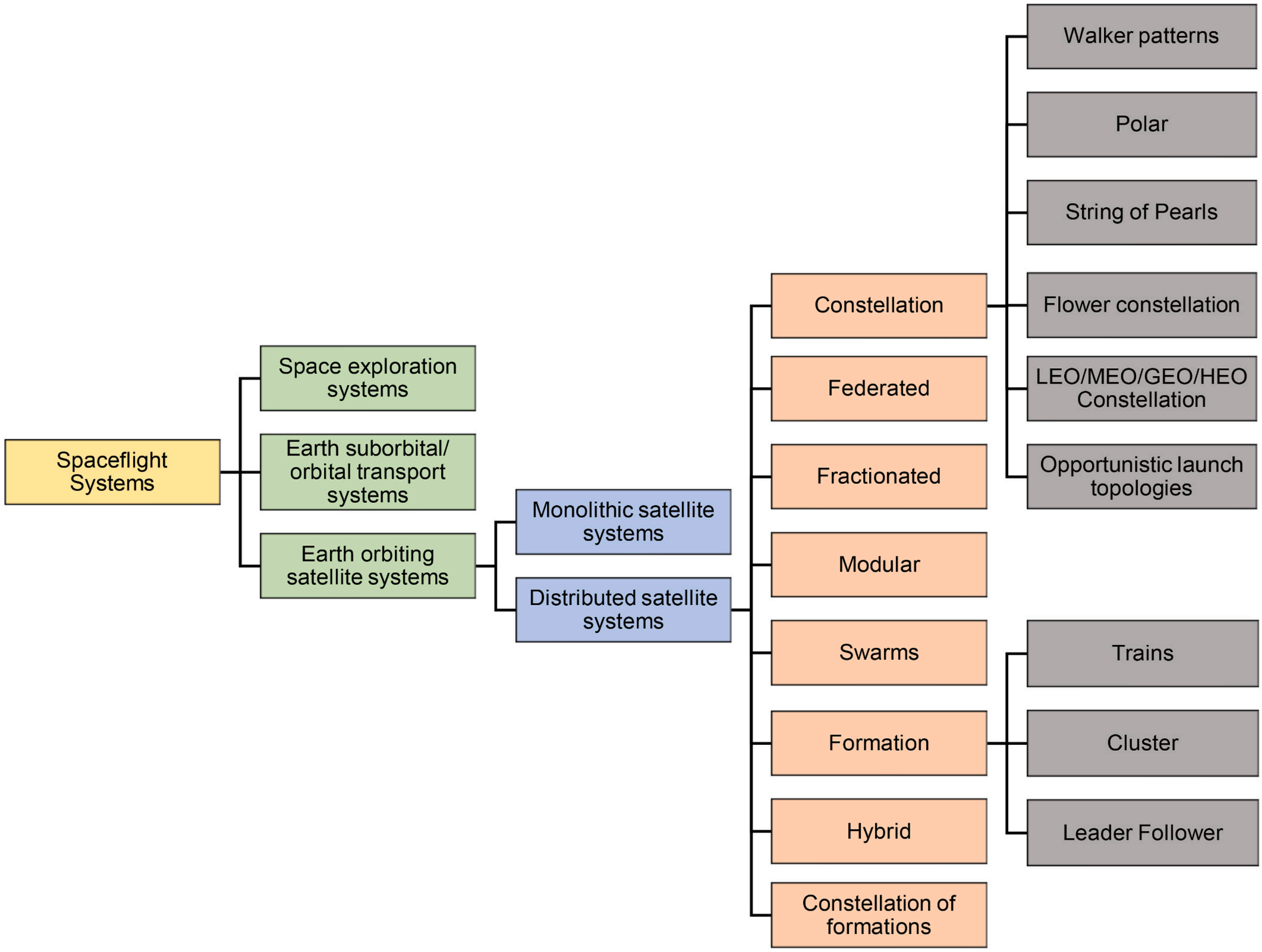

Fig. 1. Classification of spaceflight systems.

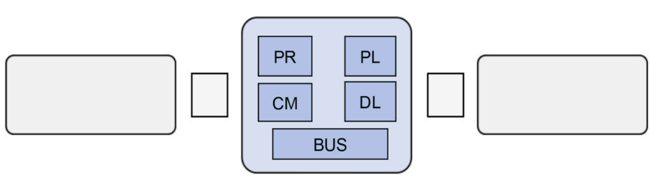

Fig. 2. Monolithic satellite system. Adapted from Ref. [14].

system-wide failure [28]. A disturbance to one component, on the other hand, may be best controlled in a system with a high level of modularity. Modularity is often explored as a spectrum of several levels and forms of a system that exist as a continuum within the system and not a binary property [29,30]. Further, continuous modularity can be intuitively and methodically represented and quantified for some satellite systems that are now being introduced for a subset of elements in a network system [27,31].

In accordance with the broader concept, we can introduce a framework consisting of five DSS modularity levels identified from M_0 to M_4 in Fig. 3. This discretization allows for better computational tractability and comprises fully integral architectures (M_0), integral yet decomposable architectures (M_1), modular yet monolithic architectures (M_2), static distributed architectures (M_3) and dynamic distributed architectures (M_4). A set of value operators quantify the net operator (M^+), which shifts between two neighbouring levels in this spectrum. When used in conjunction with M^+ operators, the spectrum can help designers choose appropriate parameters and put together a system-specific computational tool using a number of pre-existing tools and approaches [14,26,30–32].

The transition from M_0 to M_1 is referred to as *Decomposition*, from M_1 to M_2 as *Splitting*, from M_2 to M_3 as *Fractionation* and from M_3 to M_4 as *Resource Sharing*. In satellite architecture, M_0, M_1 and M_2 are considered monolithic systems, whereas M_3 and M_4 represent distributed architecture systems. While M_0, M_1 and M_2 cover all instances of modularisation for monolithic systems (systems with only one physical unit), M_3 and M_4 cover systems with multiple units (distributed systems) and the possibility of communication between them [33]. M^+ operators effectively transform the conceptual framework into a computational decision-making tool, which allows to implement the best level of modularity for a certain system's functionality in a given mission environment. The decision-making paradigm entails both the modularity phase and the design implementation inside that phase. By including a set of operators (M^+ operators) for calculating the transition value from one stage of modularity (M_x) to its next immediate phase (M_{x+1}), we focus on the former. By computing the probability distribution of the difference in value between two consecutive phases, the suggested decision-making operators evaluate the performance of the system before and after operation [33]. This will allow decisions to be taken based on an average value difference as well as the level of risk tolerance. For most engineering systems, M_1 is the lowest modularity, so the splitting operation suggests the changeover from M_1 to M_2 through the

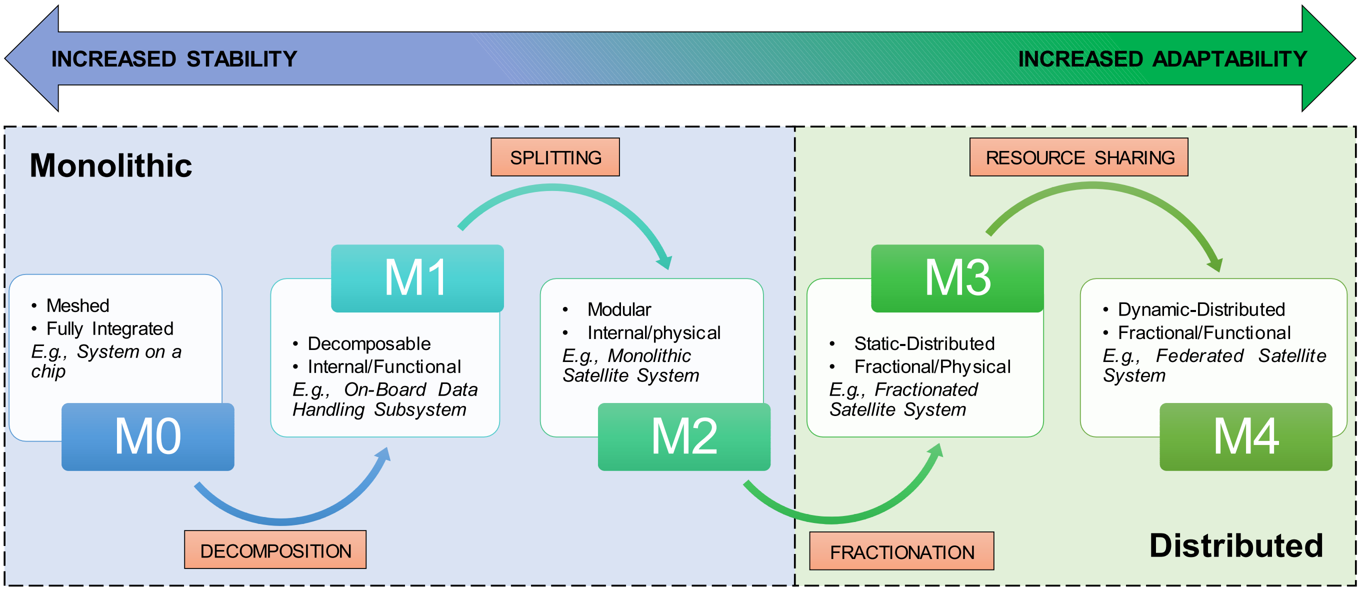

Fig. 3. A five-stage modularity with distributed architecture spectrum and four M^+ operations. Adapted from Ref. [32].

development and use of proper standard interfaces. Fractionation operation by shifting one or more of its subsystems to other fractions takes a system from M_2 to M_3. Although M^+ evaluation specifics a procedural algorithm which is dependent on particular systems and its parameters, which acts as a decision-making evaluation engine [32].

The M^+ value is measured by comparing the system's value prior and post its operations. Such assessment involves knowledge of the system and its settings [14,26,27,30,32,33]. Fig. 4 shows the input and output characteristics for evaluating M^+ operators. At each level of modularity, the system's value is determined using one of the common system assessment methods (e.g., discounted cash flow analysis, scenario analysis), while taking the subsequent criteria into account [32,33]:

a) **Technical Parameters:** For instance, the probability density of a failure, the time required for an upgrade to become available, the highest number of modules allowable and the maximum transmission bandwidth permitted.
b) **Economical Parameters:** For instance, the user demand in terms of number of modules at a given time, the cost of launching and operating a module and the rate at which distinct module types generate value.

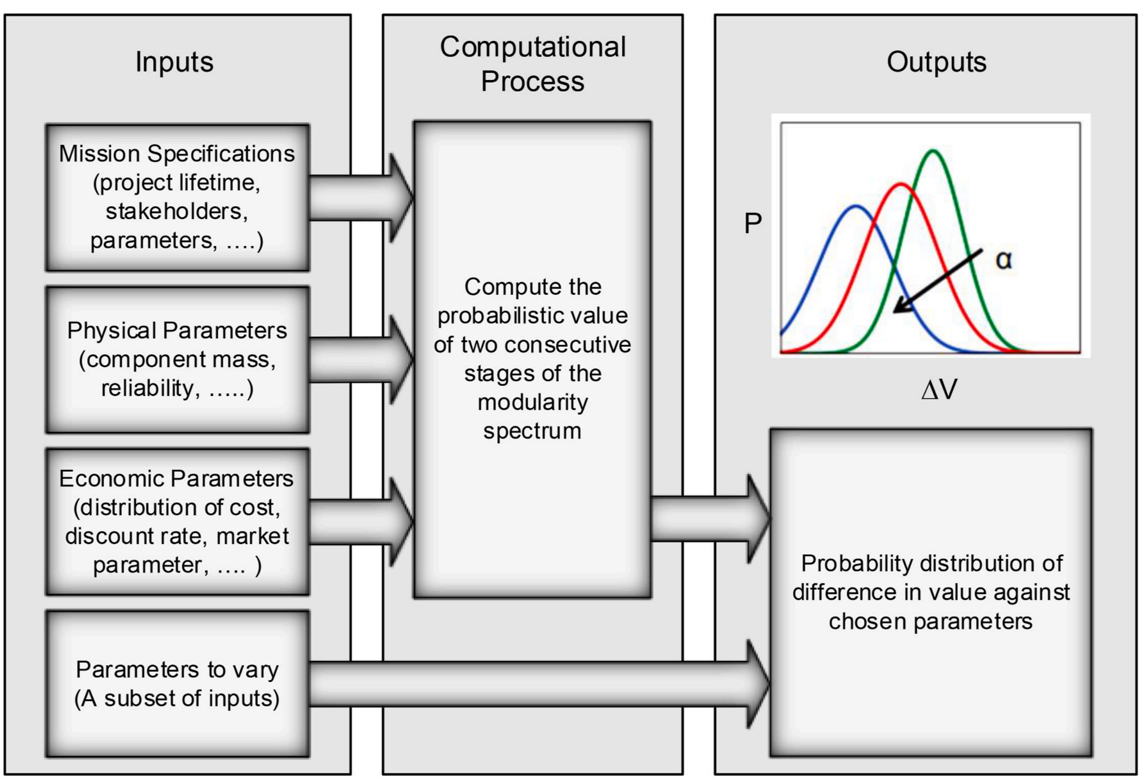

Fig. 4. Quantification of the M^+ operation value. Adapted from Ref. [32].

c) **Life Cycle Parameters:** Total time required for operation, budget, as well as maximum time required for initial deployment.

A high-level process for calculating the decentralisation values from M_3 to M_4 is depicted in Fig. 5. Because of the underlying network structure, designers are recommended to rely on multi-agent techniques that blend system dynamics and evolution with autonomous behaviour [34].

2.3. DSS classification

DSS are categorized based on the type of mission and function they perform. Activities required to meet local objectives (i.e., those specific to each module) or small bits of a global objective's functioning (i.e., particular to the infrastructure) may be included in modules performing activities in a distributed infrastructure, whether it be in independent satellite systems or distributed spacecraft. As a result, the function type is measured in terms of how dispersed the mission's goals are, ranging from no collaboration between modules (i.e., local functionality) to a fully functional symbiosis (i.e., distributed functionality). As a result, different DSS missions are characterised according to their degree of distribution in terms of the system's capabilities or goals and resource interdependence between modules. A bi-dimensional classification can be introduced by considering these two domains, as shown in Fig. 6, with values in the range [0,1]. The x-axis shows the degree of mission goal distribution, which ranges from missions in which satellite modules work together to advance a single global function to goals in which each satellite module develops its own local activity. The y-axis shows the degree of fractionation among scenarios where modules are totally reliant on one another and cases where nodes are completely resource self-sufficient [35,36]. Both classification axes are independent. The following are more specific classifications of DSS which will be discussed in the following subsections:

- Constellations
- Fractionation
- Federated
- Modular
- Swarms
- Formation
- Constellation of formations
- Hybrid Missions

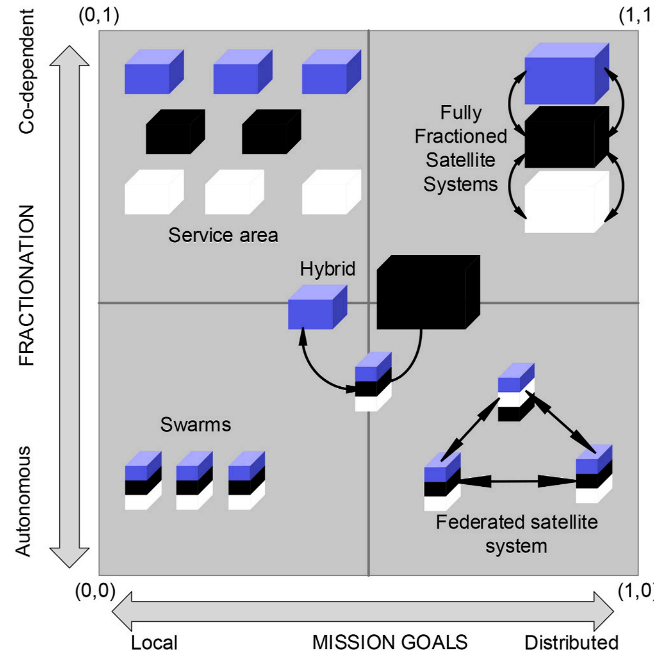

Fig. 6. DSS classification. Adapted from Ref. [36].

2.3.1. Constellation

A satellite constellation is a collection of homogeneous or heterogeneous spacecraft that operate as a unified system, with the purpose of providing continuous global or near-global coverage as shown in Fig. 7 (a). Satellites are usually positioned among a set of orbital planes that are complementary to one another and are connected directly or via other satellites to one or multiple ground stations across the world. The literature provides wide coverage of satellite constellations [22,37–40].

2.3.2. Fractionation

In fractionated systems, a spacecraft is divided into smaller units collaborating to achieve a common mission objective. The satellite consists of co-dependent modules that require system resources to be exchanged in order to function as shown in Fig. 7 (b) [41]. While all fractionated systems need a common infrastructure consisting of data processing, power, communication link, etc., to complete the functions calling for dedicated fractions to provide these services, two extremes can be thought of based on task achievement. At one end of the spectrum, distinct spacecraft tasks are carried out by its units. Though there

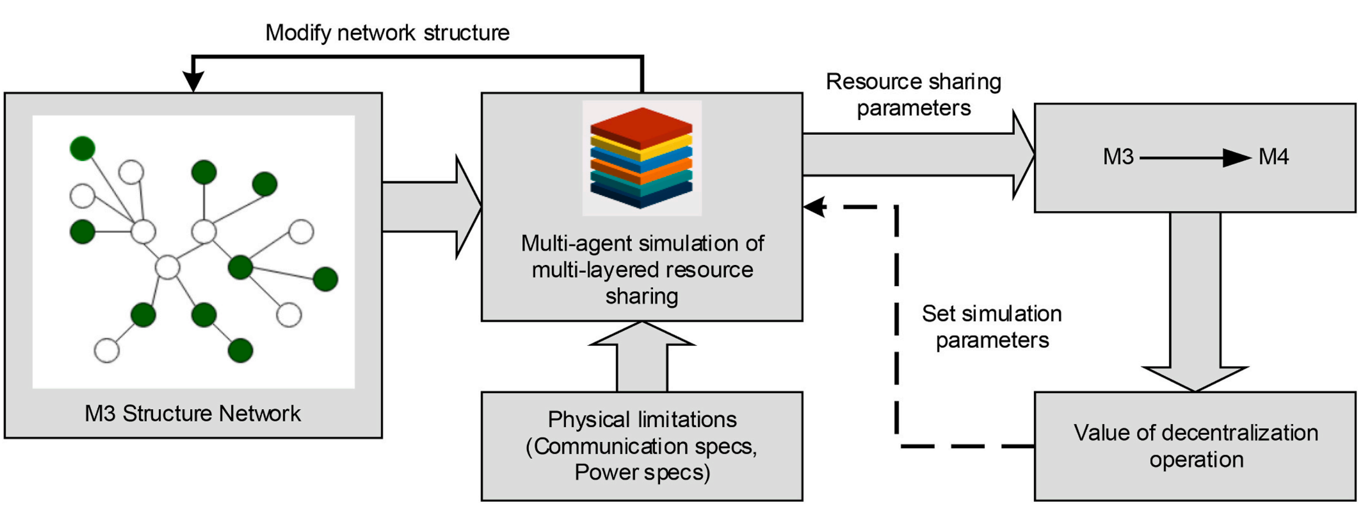

Fig. 5. Calculation of the decentralisation operation (M_3 to M_4) value. Adapted from Ref. [32].

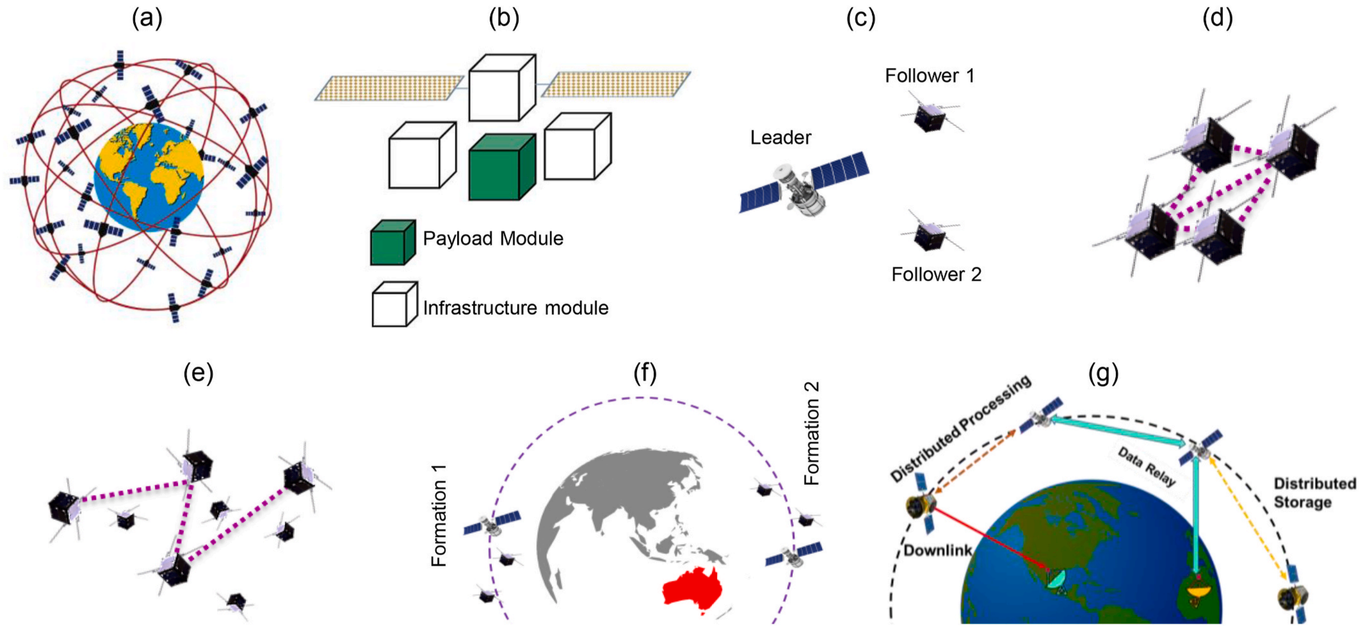

Fig. 7. DSS types (a) constellation (b) fractionated (c) formation (d) cluster (e) swarms (f) constellation of formation (g) federated.

is minimal cooperation between them, each unit is still highly dependent on the infrastructure. At the other end of the spectrum, fully fractionated systems have modules which collaborate on accomplishing the same task towards the global mission objectives. There is a considerable resource dependency in this scenario and functionalities of the modules [36,42–47].

2.3.3. Federated system

In a federated system, a group of satellites work together to provide a specific service, but each satellite operates independently, with its own mission and communication capabilities. A Federated Satellite System (FSS) is a network of satellites that coordinate by exploiting the potential of their resources, with each satellite having all of the infrastructure needed (i.e., not a fraction) to operate and so being completely self-contained. Independent satellites are built and placed in orbit for specific objectives, allowing them to employ their resources and capabilities for an opportunistic distributed mission [48]. Federated satellites are simply another example of fractionated spacecraft, as they combine some of their capabilities and resources for a global mission [48–51]. Because the transferred resources are always underutilised in a module's primary mission, the nodes are complete and form heterogeneous systems, allowing for a new category of distributed satellite missions to be categorized, as shown in Fig. 8 [36].

2.3.4. Modular system

Modular systems are more far-fetched DSS characterized by

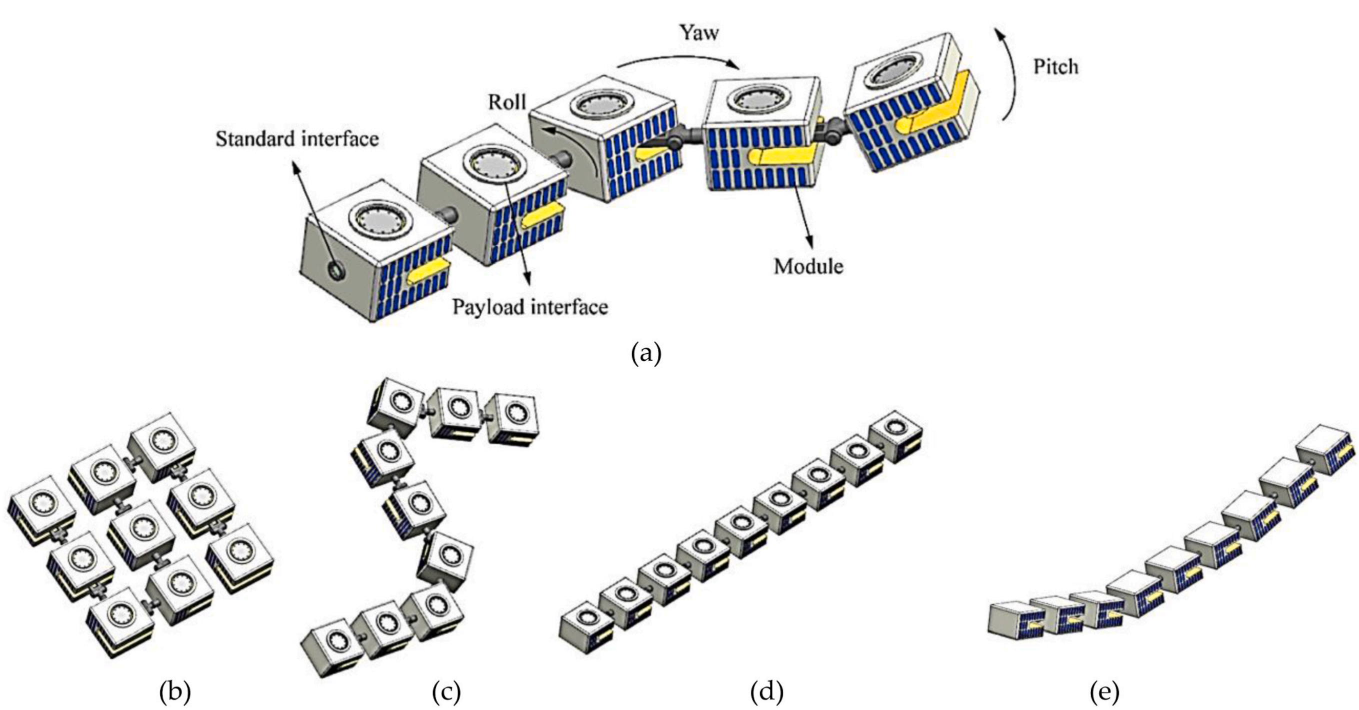

Fig. 8. Concept of SMSRS (a) and deployment stages: (b) folded state; (c) unfolding; (d) unfolded state; and (e) working configuration. Adapted from Ref. [52].

physically joined modules as shown in Fig. 7(d). For instance, based on the CubeSat standard, Jiping et al. [52] presented a new type of DSS with a reconfigurable construction and customizable function, dubbed Space Modular Self-Reconfigurable Satellite (SMSRS) design concept. The following are some of the features of SMSRS: (1) modularity; (2) scalability; (3) structural reconfigurability; (4) fault tolerance; and (5) functional adjustability. Fig. 8 shows the SMSRS configuration and the various deployment stages from a folded state to the working state. Optical cameras, Synthetic Aperture Radar (SAR), communication and other payloads are among the ones which can best exploit this concept: SMSRS arranges and reorganises these payloads in a variety of space orientations through structural reconfiguration, allowing it to carry out a variety of missions [52].

2.3.5. Swarms

Swarm intelligence enables natural (and artificial) multi-agent systems decentralised control and self-organization capabilities as shown in Fig. 7 (e). Bloom [53] coined the term while researching complex adaptive systems and it is made up of several principles (distributed parallel processing, super organism, group selection, apoptosis). A typical swarm system has specific characteristics, such as a large number of homogenous agents that interact with one another via fundamental rules that exploit only local information. Information is exchanged either directly with another agent or indirectly through the environment. Stigmergy is the name given to this indirect coordination mechanism [54]. The system's overall behaviour results from the coordinated interaction of the various agents. In these systems, individual behaviour is commonly described in probabilistic terms, as a result of local neighbourhood perception [55]. These characteristics allow a multi-objective optimization of the swarm that maximizes scalability, parallelization and fault resistance. Swarms are very adaptable while also being extremely resilient (the system continues to work even if certain components fail) and completely decentralised. It works whether they are being used to describe natural or human-made agents. Satellite swarms are distributed missions in which the infrastructure modules are autonomous satellites performing their own functions/tasks without the interchange or collaboration of resources (such as data). A distributed satellite of this sort is made up of homogenous modules [56]. By increasing the number of modules dedicated to a certain task (i.e., by adding redundancy), the set of constellation-conforming modules increases the system's usability, which benefits the system's robustness. For example, a deteriorating sensor in one of the modules of an EO mission, does not prevent the operators from obtaining images. However, the amount of resources transferred (i.e., power, computational resources) is almost minimal in this situation. This type of distributed spacecraft can still communicate with one another to preserve the intended formations and to relay critical trajectory information (e.g., to avoid collisions within the swarms) [35,56–58]. Nonetheless, their functions are limited to local neighbours and their activities are done autonomously without transferring any resources altogether [35,36].

2.3.6. Formation

The coordinated motion of multiple satellites is known as satellite formation flying. In an effort to match the user's requirements, different formations are possible. Satellite formation flight entails many architectures depending on geometric configuration, operational arrangement and other characteristics [59,60]. The main operational arrangements are:

- **Cluster formation:** A cluster configuration occurs when a set of satellites are organised in a close formation and positioned in orbits that keep them nearby each other. Satellites in a cluster normally travel close together; which is different from trailing formations [46,59].
- **Trailing formation:** Satellites share the same orbit and therefore follow one another on the same path. The satellites are configured to maintain a predetermined relative angular separation in their orbit. It is worth noting that the relative angular spacing in circular orbits remains constant throughout. The relative angular spacing in elliptic orbits, on the other hand, changes depending on the satellite's location. Normally, these angles are determined when a particular satellite (denoted as primary) is at the perigee [59].
- **Leader-Follower formation:** This arrangement occurs when one spacecraft is designated as leader and one or multiple other spacecraft are forced to fly in formation with the leader. It should be noted that the literature uses a variety of terms when referring to this arrangement, including: (i) chief-deputy; (ii) master-slave; (iii) mother-daughter ships; (iv) primary-secondary; and more [23,59,60].

2.3.7. Constellation of formation

A constellation of formation combines the characteristics of formation flying satellites and constellations. It is therefore a set of formations, each of which has a flight coordination between neighbouring satellites. In the constellation view, each formation can be described by the centre of mass of each formation, flying far away from each other but with a common mission goal as shown in Fig. 7 (f). Within the formation there is typically relative navigation, guidance and control to acquire and reconfigure the layout. On the other hand, the constellation objective is defined in terms of the orbit of a reference satellite (sometimes called chief) or some weighted position average as the centre of mass of each formation in the constellation. It shall be noted that each satellite must obey to two objectives: to keep relative the formation and to remain in the constellation.

2.3.8. Hybrid mission

Hybrid mission architectures are the theorized new frontiers of the DSS concept and therefore entail a mix of distributed systems, which bridge the gaps between the previously discussed concepts and are therefore located around the centre of the bidimensional classification in Fig. 6. For instance, fractionated satellites are capable of forming a constellation with other satellites (fractionated satellite swarm) or cooperating with other units in more heterogeneous and complex situations (federation of fractionated satellites). It is worth mentioning that some DSS can change their typology in certain situations, depending on the mission goals set by the ground segment [35,36]. The objectives of hybrid missions may alter because of technical issues (e.g., unit maintenance, repair and replacement, research potential) or for commercial reasons (exploitation of modules, sporadic provision of services). Federated satellite systems with modules that can function individually or in formation in flight are a good example of this dynamism [36].

2.3.9. DSS architectures and classifications

Table 1 provides a detailed description of different types of DSS architecture. Within the table, *homogeneity* is defined as the degree of similarity between satellites within a DSS. On the other hand, the level of the operational independence of a satellite or a fraction of distributed spacecraft is characterised as *Operational/Functional Independence* [12,16,35,61].

A Distributed Spacecraft Mission (DSM) is a mission in which numerous spacecraft/modules work together to achieve one or more common objectives. This broad definition of DSM intends to avoid specifying whether the multiple modules/spacecraft are launched simultaneously, achieve common goals by design or ad hoc (i.e., application-driven), or if the common goals are scientific. Jacqueline et al. [62] studied a variety of DSM attributes, classified them according to the taxonomy shown in Fig. 9 and defined all the concepts used in this taxonomy.

2.4. DSS functional architecture

A methodology for bottom-up design of a distributed architecture is

Table 1
Summary of distributed architecture classifications. Adapted from Ref. [16].

DSS architecture		Mission goals	Cooperation	Homogeneity	Operational/Functional Independence
Constellation		Mission goal shared (Iridium, GPS)	Cooperation is required to support the mission goals	In general, homogeneous components, some differences possible (GPS generations)	Autonomous
Formation	Trains	Mostly Independent, but could be shared	Cooperation from optional to required	Heterogeneous components	Autonomous
	Clusters	Mission goal shared	Cooperation is required to support mission goals	Homogeneous components	From autonomous to completely co-dependent
	Leader-Follower	Mission goal shared	Cooperation from optional to required	Heterogeneous components	From autonomous to completely co-dependent
Swarms		Mission goals shared	Cooperation required to support mission goals	From homogeneous to heterogeneous components	From autonomous to completely co-dependent
Fractionated		Shared mission goals	From optional (service areas) to required (distributed critical spacecraft functions)	Heterogeneous components	From autonomous to completely co-dependent
Federated		Independent mission goals	Ad-hoc, Optional	Heterogeneous components	Autonomous
Modular		Mission goal shared	Cooperation is required to support mission goals	From homogeneous to heterogeneous components	From autonomous to completely co-dependent
Hybrid		Mostly Independent, but could be shared	Ad-hoc, Optional	Heterogeneous components	From autonomous to completely co-dependent
Constellation of formations		Mostly shared but could be independent	Cooperation is required to support mission goals	From homogeneous to heterogeneous components	From autonomous to completely co-dependent

presented, where elements of each layer are built up to reach the desired distributed architecture. The basic units arise from the bottom layer's objects and elements. At the top, there is a launch plan that shows which vehicle will launch each module [47]. DSS hardware and software architecture is discussed in the following sections.

2.4.1. Hardware and software elements

DSS hardware includes service avionics and mission-specific systems, which typically combine payload instruments and supporting infrastructure [11,12,35]. Hardware architectures are modular and expandable due to the inherent characteristics of the DSS. A possible space segment hardware arrangement is shown in Fig. 10 [14], while a modern EO DSS control segment is shown in Fig. 11. In this particular configuration, cloud-based mission control is used for planning and scheduling purposes. Payload schedules and task allocations can be defined by direct ISL data sharing, ground control uploads, or both [20, 21].

Historically, spacecraft implemented a centralized data-bus architecture, including a single On-Board Computer (OBC), normally redundant. Modern spacecraft, on the other hand, employ a number of OBC modules, interconnected through either distributed, federated or modular data networks. Software architecture for DSS is characterized by integrating some level of system autonomy, where the components interact to:

i. Distribute tasks between modules/components of satellites;
ii. Allocate infrastructure resources;
iii. Perform task scheduling in a distributed manner as per requirements.

An exemplary DSS software architecture is shown in Fig. 12, where the corresponding hardware modules are not homogenous, indicating they have different computational capabilities and availability times (i. e., system encapsulation). The system consists of various autonomy management entities (i.e., task planners) that interact to operate each spacecraft in synergy with one another. The Distributed System Layer (DSL) provides a common communication link between global and local entities [36]. The entire architecture entails two control levels in a master-slave hierarchical relationship: (1) the global control level, which is mainly relative to the software infrastructure domain; and (2) the local control level, which is relative to each module domain.

In recent times, software architectures have evolved to suit multiple and dynamically evolving operational environments [63]. Consequently, DSS control architectures are also evolving to include dynamic management policies [64]. For instance, the Local-Global paradigm just discussed is a mixed management policy, which is intended to provide an adaptive planning solution to an arbitrary number of autonomous heterogeneous distributed spacecraft modules (i. e., payloads, computational capabilities, ISL, etc.) [36]. In a DSS with dynamic management policy, the top-level "multiple-tasks multiple-modules" mission problem is translated into a "multiple-tasks single-module" arrangement by decomposition, as depicted in Fig. 13. Once the allocated sub-tasks are completed by the individual modules, their results are combined to synthesize the final solution.

3. Autonomous operation in space

Autonomy is generally associated to a system's ability to function without direct human interference, though it is a spectrum with several levels and grey areas. Therefore, in a system's context, autonomy can be defined as the ability to make informed, reasonable, self-reliant and self-determined decisions. A system should be able to sense, think and act within its surrounding environment in order to be deemed autonomous, therefore necessitating the capacity to detect its surroundings as well as some awareness of one's own powers and how they affect one's environment and internal states. The autonomous inferences and conclusions shall be drive by its own goals and necessary actions to achieve them [65]. Additionally, an autonomous system shall be capable of reacting to non-nominal conditions by adjusting its behaviour to fulfil its goal while remaining safe and secure. The degree of autonomy that a system achieves can be defined by the degree of off-nominality that it can handle and the level of abstraction of its objectives [66]. Some autonomous systems in aerospace carry out predetermined acts that do not alter in response to the environment (automatic). Other systems (automated) initiate or modify their behaviour or output in response to environmental feedback, while more advanced systems (autonomous) combine environmental feedback with the system's own interpretation of its current situation. Due to the need for reasoning regarding own and environmental states, increased autonomy is usually associated to increased "intelligence" or even "AI" for a specific mission and equated with greater capability to adapt to the environment.

3.1. Sense-think-act and layered architecture

A closed-loop ("sense-think-act") system, as illustrated in Fig. 14, describes an autonomous (machine) device or function for a layered

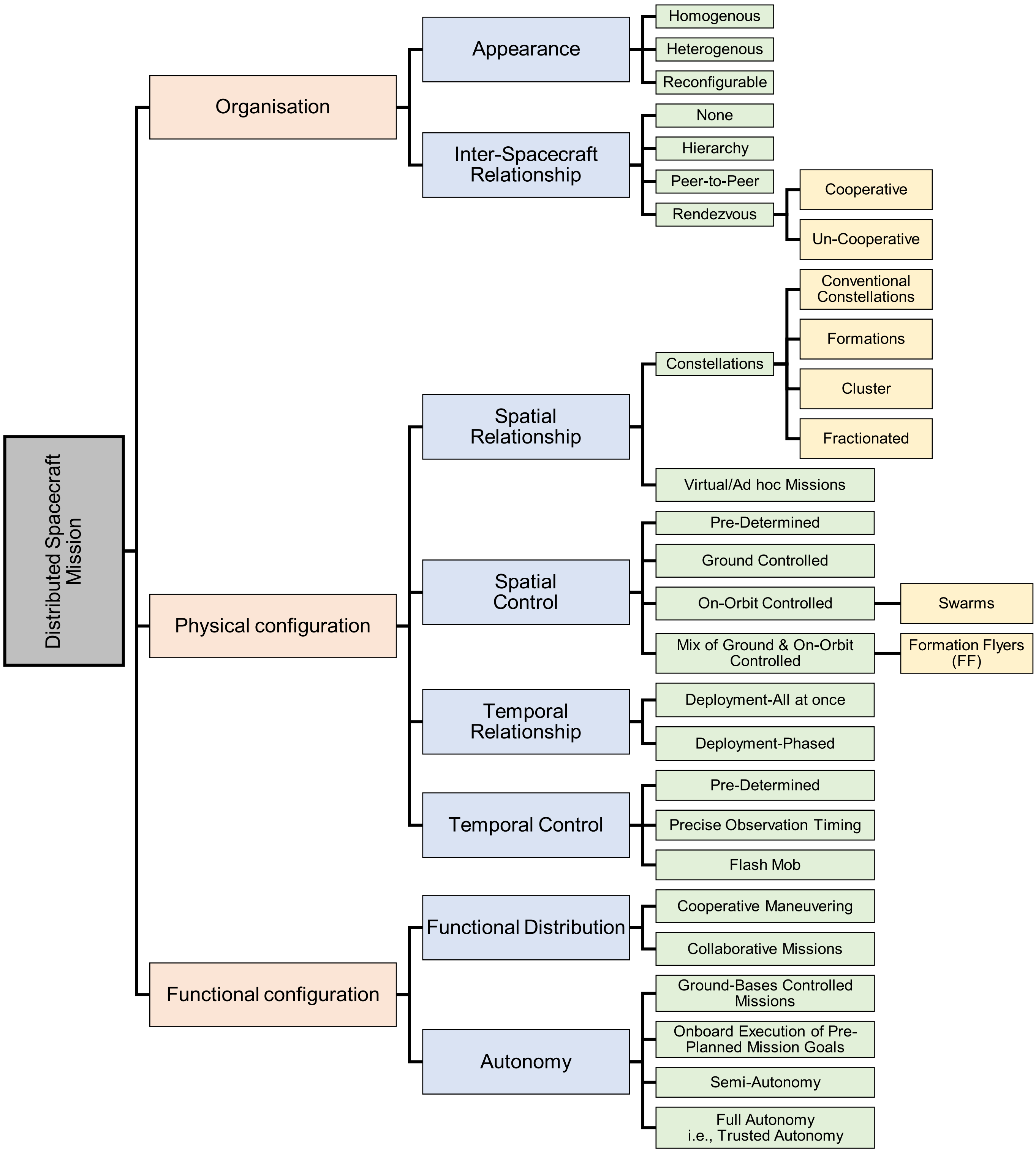

Fig. 9. DSM classification. Adapted from Ref. [62].

architecture where the fundamental tasks are:

- Sensors ("sense"): gathering data from lower levels or hardware and transferring it to a representation that the software can understand;
- Control ("think"): weighing sensory data, spacecraft information and desired outcomes before deciding which actions should be enacted;
- Actuation ("act"): execute the operation that was determined by the control analysis process (without further human interference).

The conventional layered architecture involves planning, task sequencing and reactive capabilities. Deliberative, executive and functional layers are all terms used to describe these processes and conventional thinking is that autonomy shall imbue all of these. The layers are defined by their abstraction from the real environment and the time they take to complete an iteration, with clear response-time constraints as a function of the time horizon that can be considered. The functional layer has fast turnaround requirements since this must maintain pace with hardware sensors and actuators, and each component normally

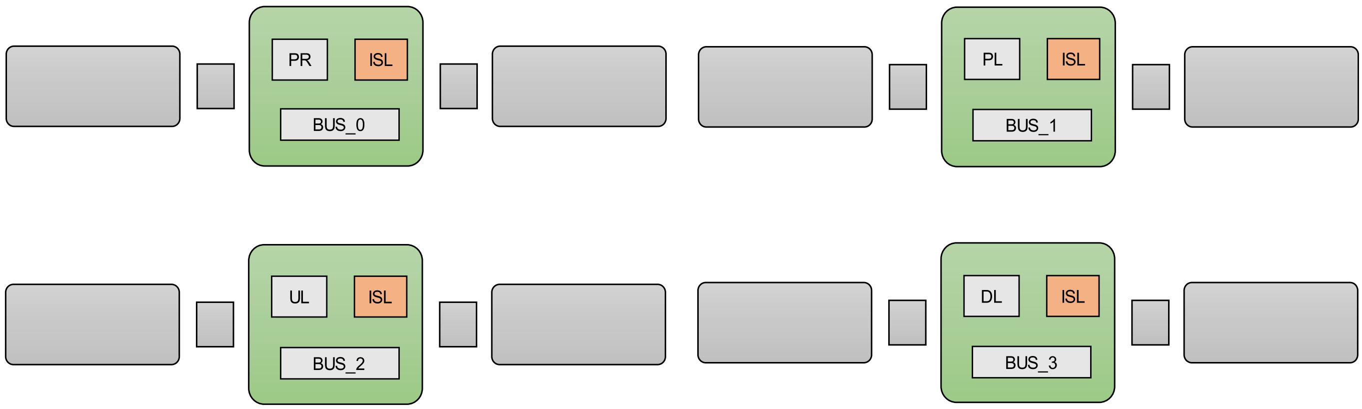

Fig. 10. DSS architecture. PR: Processor, DL: Downlink, PL: Payload are fractionated and distributed and connected through ISL. Adapted from Ref. [14].

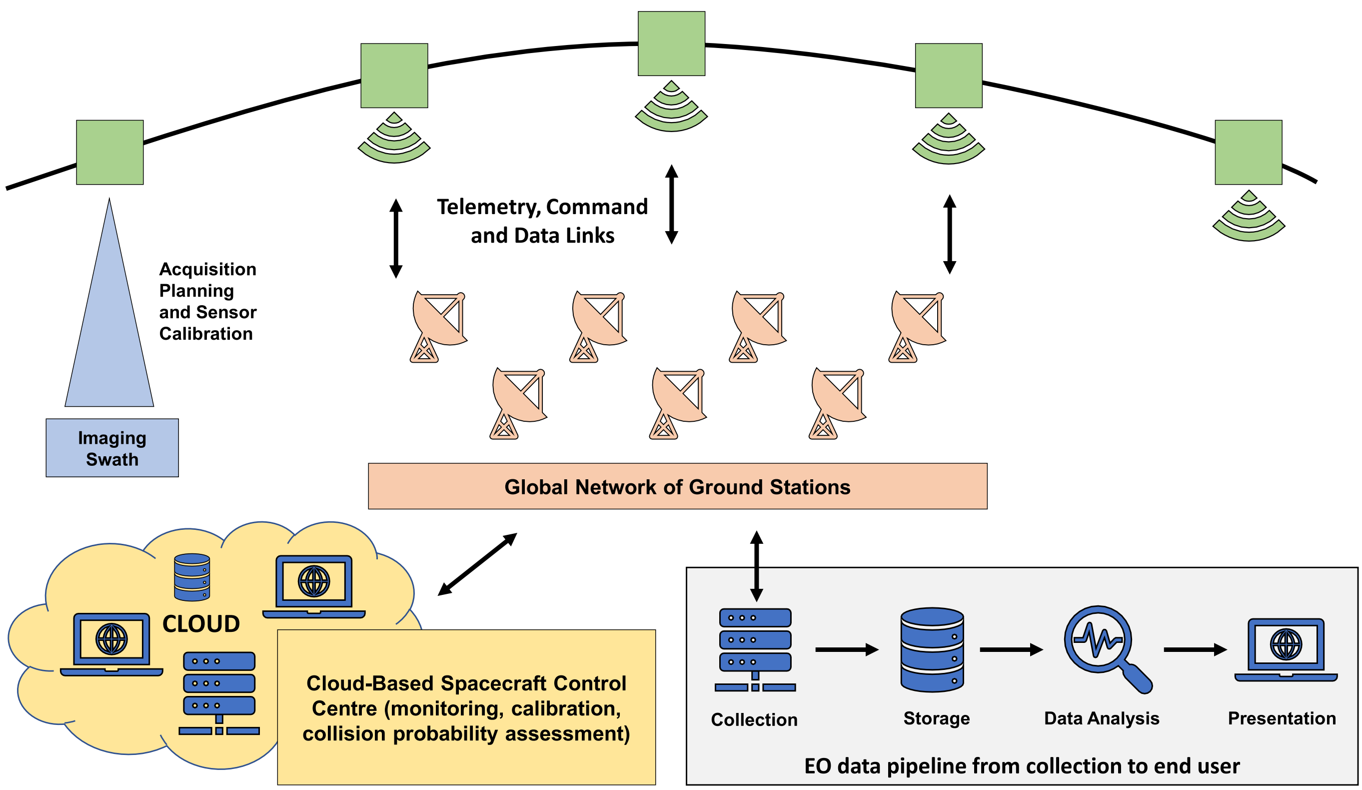

Fig. 11. DSS architecture entailing cloud-based control segment. Adapted from Ref. [20].

only considers one task or series of tasks. The executive layer manages a collection of tasks at the moment and it only needs to reply fast enough to meet task action potentials and terminations. Finally, the deliberative layer takes into account many tasks and multiple possibilities, as well as future repercussions. It just needs to reply quickly enough to offer the executive extra job sets or plans when necessary. On the other hand, the layers do not just indicate a boost in capabilities; trade-offs do exist. The functional layer has access to detailed data about the hardware and frequently performs complex numerical calculations to decide responses or provide data to the layers above. The executive layer usually includes contingency management and control skills that the deliberative layer lacks. Each layer executes a variation of the sense-think-act cycle in an autonomy system. The overarching system of autonomy has a sense-act-think cycle as well [67].

When looking at autonomy in space, the European Cooperation for Space Standardization (ECSS) has defined four degrees of capability, with level E4 being the most autonomous. Only level E4 compatible technologies can be deemed genuinely autonomous, according to the criteria in Table 2, whereas levels E1 to E3 relate with human-operated or automated systems. Unlike autonomous systems, automated systems can only deal with scenarios that their designers have predicted. These systems will react to these conditions using so-called on-board control procedures, which are pre-programmed sequences of operations (i.e., events). In order to operate the entire mission autonomously, there is a need for autonomy in mission data management and mission fault management. ECSS defines these capability levels as in Table 3 and Table 4 [68]. Both Earth-orbiting and deep space missions require the use of robotics and autonomy. Most spacecraft operations' control functions and procedures are transmitted for immediate execution by telecommand or, more commonly, in precisely organised sequences at specified times. Almost all remote sensing satellites, for example, gather images and downlink these to Earth at predetermined geographic areas while retaining the correct attitude using on-board sensors and reaction wheels. On the other hand, Astronauts operate robotic systems in space,

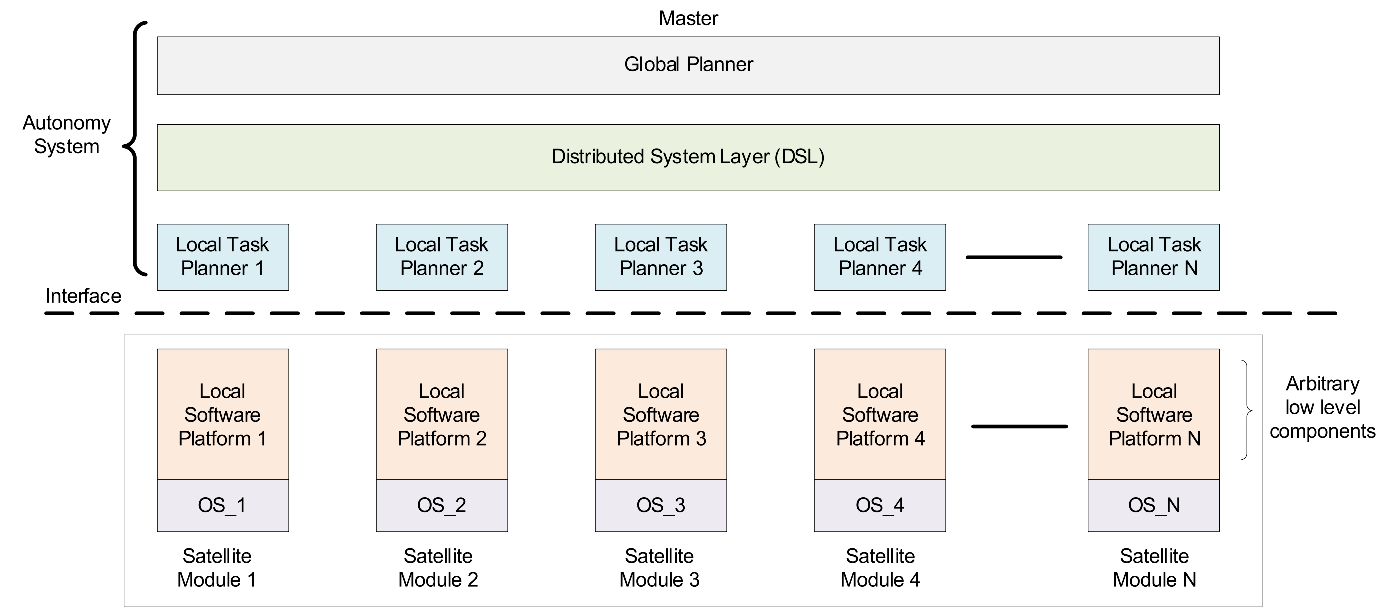

Fig. 12. Distributed software architecture. Adapted from Ref. [36].

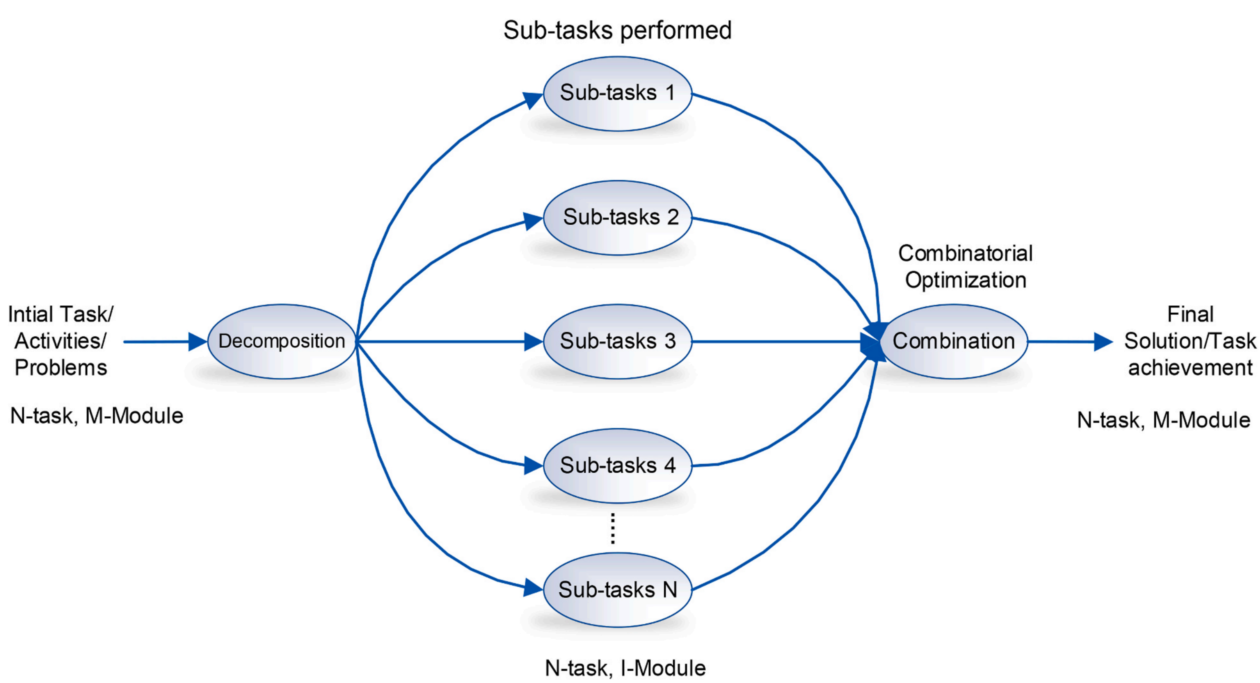

Fig. 13. Task execution in a distributed system. Adapted from Ref. [36].

such as the Canada arm Remote Manipulator. Few autonomous aerospace systems make the decisions without human intervention in order to attain high-level objectives. Variable autonomy, as defined by Proud et al. [69] and Novaes [70], revolves around the concept of selecting desirable levels of autonomy while operating a space system. This allows the autonomous system or the human user to alter the level of autonomy as needed by the situation. Autonomous space systems provide excellent sensing and are therefore necessary if human usage and exploration of space are to expand in terms of both reach and complexity.

Trusted autonomous space systems will allow such activity to continue with confidence. For crucial space systems, several scenarios can be predicted. Some of these are already in the development and demonstration stages. For example, autonomous on-board data processing, on-orbit satellite servicing/repairing, analysis and decision-making for remote sensing for both defence and civil applications, as well as future human space habitation, which could include both space tourism and deep space colonisation, are all plausible scenarios [66, 71–73].

Fig. 15 shows an evolutionary roadmap of space system capabilities with a growing degree of autonomy over time. The four categories are defined as follows: (1) teleoperation (operated from Earth); (2) automatic operation (pre-programmed self-controls); (3) semi-autonomous operation (start with predefined command sequence, where machine adapts to the external environment); and (4) fully autonomous operation (autonomous decision making (goal-oriented)) [74]. Autonomy can be incorporated in various segments of the satellite infrastructure. With recent trends, TASO for space applications is becoming more popular. AI applications in the control and space segments have the potential to

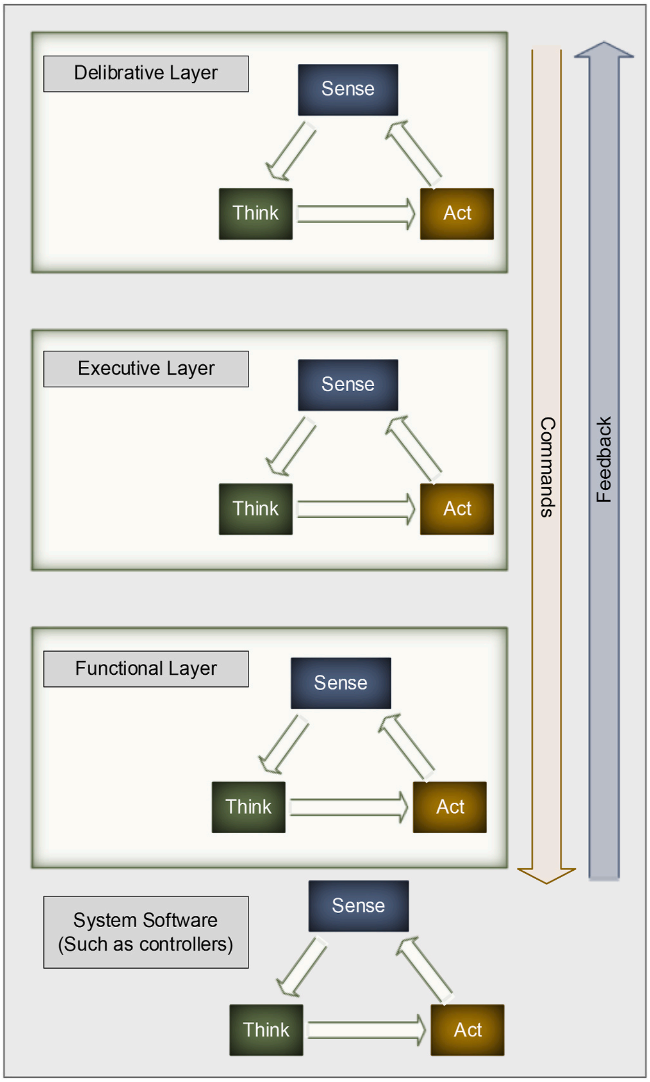

Fig. 14. The "sense-think-act" cycle autonomous system layered architecture [67].

Table 2
Levels of autonomy for mission execution according to ECSS [68].

Level	Description	Functions
E1	Mission execution underground control with limited on-board capability for safety issues	Real-time control from the ground for nominal operations Execution of time-tagged commands for safety issues
E2	Execution of pre-planned, ground defined, mission operations on-board	Capability to store time-based commands in an on-board scheduler
E3	Execution of adaptive mission operations on-board	Event-based autonomous operations Execution of on-board operations control procedures
E4	Execution of goal-oriented mission operations on-board	Goal-oriented mission re-planning

increase the value of both ground and space operations.

3.2. Human-machine interaction at increasing levels of autonomy

Since the industrial revolution, machines have been typically used as a tool to aid humans in executing tasks. Before World War II (WWII), the human-machine interaction design paradigm was based on "humans adapting to machines", whereas after WWII, ergonomics and human factors engineering studies succeeded in establishing that "machines shall adapt to humans". This has proven often challenging especially in the case of inherently non-adaptive systems because the varying complexity and pace of tasks was entirely absorbed by the human operator. The further step in this evolution is cognitive systems, where a two-way adaptive interaction between humans and the machine are possible.

Table 3
Levels of autonomy for Mission fault management according to ECSS [68].

Level	Description	Functions
F1	Establish a safe space segment configuration following an on-board failure	Identify anomalies and report to ground segment Reconfigure on-board systems to isolate failed equipment or functions Place space segment in a safe state
F2	Re-establish nominal mission operations following an on-board failure	As F1, plus reconfigure to a nominal operation configuration Resume execution of nominal operations Resume generation of mission products

Table 4
Levels of autonomy for mission data management according to ECSS [68].

Level	Description	Functions
D1	Storage on-board of essential mission data following a ground outage or a failure situation	Storage and retrieval of event reports Storage management
D2	Storage on-board of all mission data, i.e., the space segment is independent from the availability of the ground segment	As D1 plus storage and retrieval of all mission data

For decades, the HCI community has used a human-centred approach. The current generation is transitioning from human-centred design to human-centred AI, which is not a novel idea. While a technology-centric approach has dominated the development of AI technology, academics have studied a range of human-centred ways to address the particular difficulties highlighted by AI technology. Fig. 16 expands on the approach and the reader is referred to Ref. [75] for further details.

Human-Machine Systems (HMS) incorporate the functions of human operator (individual or a group) and a machine, which can be treated as a single entity interacting with the external environment (see Fig. 17). An autonomous system or function is, by definition, out of human control to some extent. Humans can, however, exert some control during the design and development stage at the point of task initiation and during service, for example, by interrupting the system's operation. HMS can be controlled in a variety of ways:

1. **Direct control**: Requires continuous interaction by a human operator to control the system's functions directly or indirectly, making it non-autonomous.
2. **Shared control**: Certain tasks are controlled directly by the human operator, while others are controlled by the machine under the operator's supervision. The aim of shared control is to:
   a. Combine the advantages of human control (global situational awareness and decision) and computer control (high-speed, high-accuracy actions).
   b. Partially overcome human control limitations (attention period and field of vision limitations, tension and fatigue) and machine control limitations (limited situational awareness and decision-making capacity, sensing uncertainties).
3. **Supervisory control**: a device executes tasks autonomously while a human operator supervises and provides guidance, intervenes and reclaims control as required.

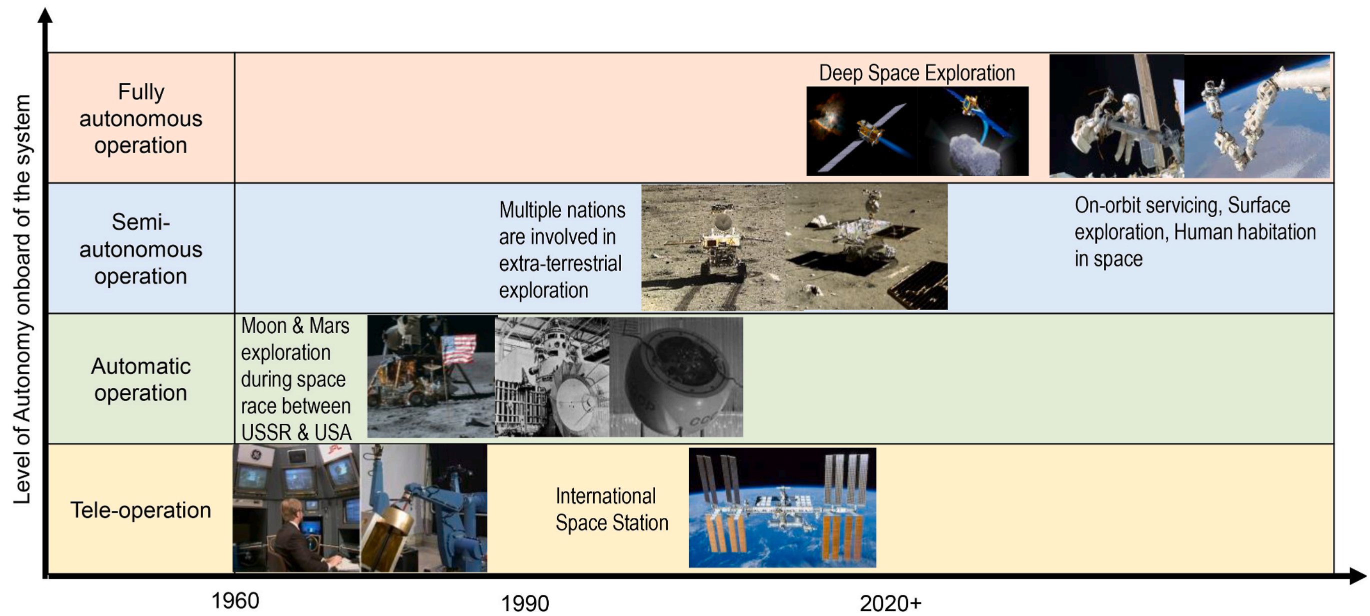

Fig. 15. Evolution of autonomy in space systems. Adapted from Ref. [74].

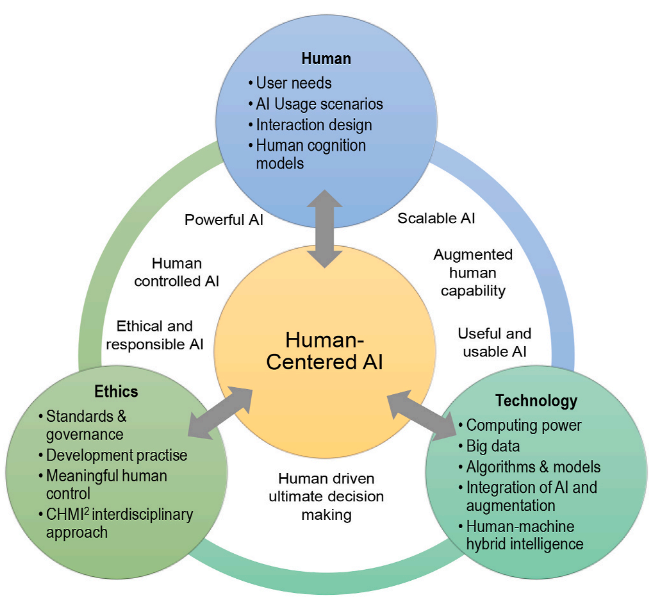

Fig. 16. Framework for human-centred AI. From Ref. [75].

Supervisory control is often used in applications where direct or shared control of a machine is not feasible due to communications delays between both the operator's commands and the system's corresponding operation, such as in systems working in outer space or deep-sea areas.

The autonomy of a machine influences the number of tasks it can complete as a result of the demand and regularity of human-machine interaction. From the human interaction perspective, the levels of autonomy vary from teleoperation to complete autonomy. Beer [76] proposes a structure for categorising levels of autonomy and guidelines for choosing and maximising the appropriate level of human-machine interaction centred on the machine's intended purpose. The categorisation is shown in Table 5. Humans are involved at all levels except the final stage of autonomy where in the aerospace context it is more appropriate to refer to trusted autonomy [77].

3.2.1. *Human-on-the-loop control*

Autonomous control is challenging in most real-world environments because the operating environment is complex, unpredictable and dynamic in nature. Human supervisory control, on the other hand, allows operators to exert some control through "human-on-the-loop" monitoring and intervention (as opposed to "human-in-the-loop", which conventionally refers to direct control). There may be several loops in which the operator may intervene, each with different outcomes, ranging from lower-level roles (monitoring and amending machine resolutions) to higher-level strategic tasks (planning evolving mission goals and operational constraints). In any case, successful human-on-the-loop monitoring and intervention necessitate constant situational awareness as well as sufficient time to intervene (i.e., override, deactivate, or take other actions) and a way to interfere, such as a permanent contact connection (for remotely operating systems) and/or direct physical controls that allow the user to regain control or deactivate the machine. Unfortunately, even though the human-on-the-loop model meets all the above requirements, it is not a silver bullet for maintaining successful control over autonomous systems due to well-known human-machine interaction issues. These include:

1. Over-trust in the system, or automation bias, occurs when humans tend to put too much confidence in the operation of an autonomous machine;
2. The diminished awareness by the human operator(s) of operational and environmental conditions due to not being directly tasked to address these;
3. The ethical buffer, in which the human operator delegated moral obligation and accountability to the system, which is viewed as a valid authority.

3.2.2. *Adaptive and cognitive HMS*

There is no universally accepted models and optimality criteria for human interaction with autonomous systems. The need for human supervision and the acceptable level of autonomy is related to the complexity of the environment wherein the system operates as well as the complexity of the role it executes. It is common understanding that the higher the complexity of the task and/or the environment, the greater the challenges for autonomy design and verification, particularly for safety-critical tasks and environments in which a system failure may cause fatalities, injuries or property damage. This is one of the critical

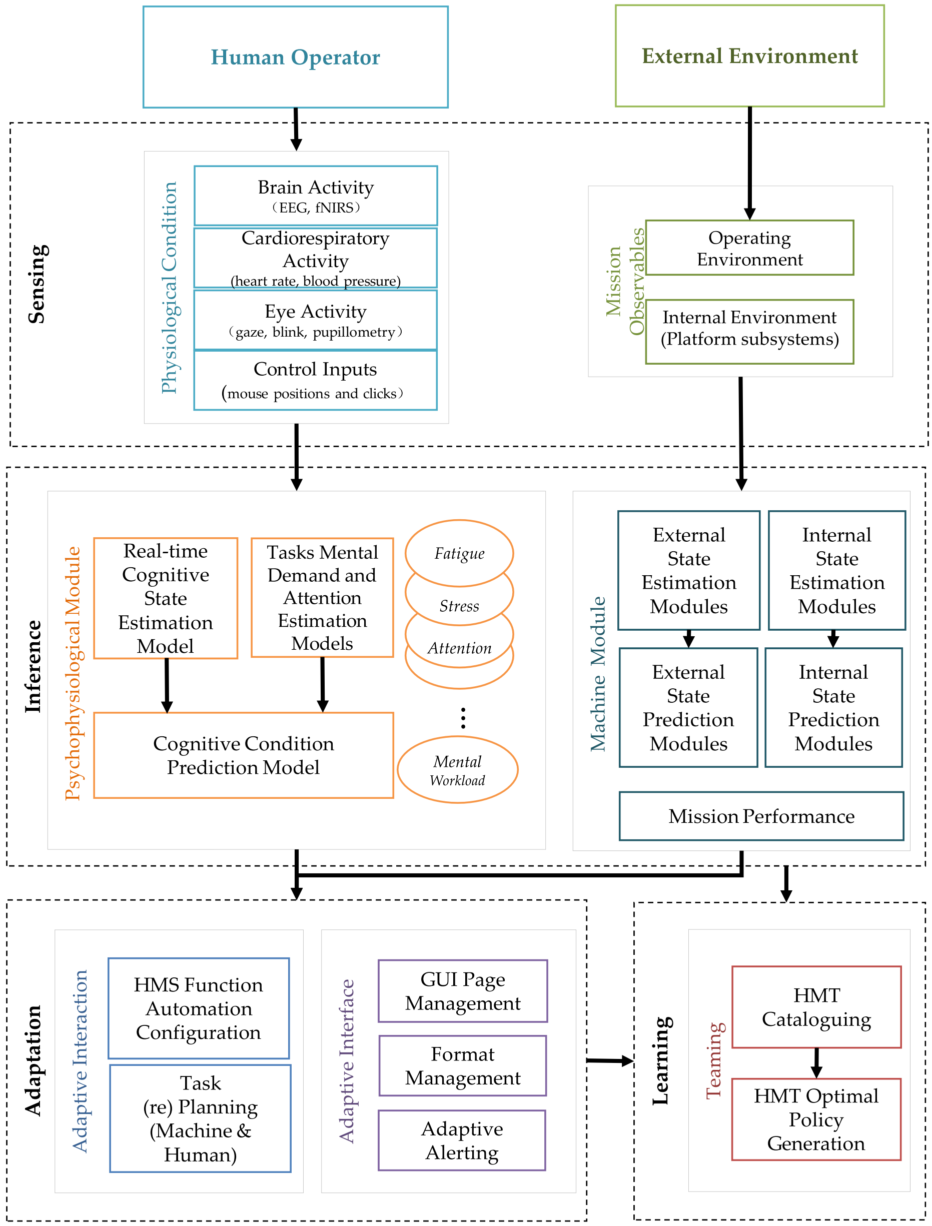

Fig. 17. CHMI^2 framework [85].

aspects that will be addressed in evolving safety certification standards, such as the evolutions of SAE and MIL-STD-822F [77,78]. When a poorly designed autonomous system is used in an unpredictable, uncontrolled environment, there is a high risk of failure with unforeseen consequences. Nonetheless, recent technological advancements in complex control software, such as AI techniques, improve the adaptiveness of the system and therefore increase the degree of autonomy that can be successfully implemented for more complex tasks in complex environments.

Cognitive Human-Machine Interfaces and Interactions (CHMI^2) is a new concept to human factors engineering in aerospace that incorporates adaptive functionalities into the design of the operator's command, control and display capabilities [79,80]. A CHMI^2 system evaluates human cognitive states built on critical psycho-physiological observables being measured [80]. The cognitive states have been utilised to estimate and improve the operator performance in the accomplishment of tasks to improve the efficiency and effectiveness of the overall human-machine teaming. Moreover, the result in the literature [80] indicates that higher levels of CHMI^2 supported automation are beneficial for space applications.

In space applications, CHMI^2 functionalities can improve the operational effectiveness of spacecraft operation as well as improve the overall safety and effectiveness of operations [80–82]. CHMI^2 supports human-machine teaming, whereby a system senses and adapts to the mission environment and the cognitive state of the operator. The CHMI^2 concept supports Trusted Autonomous Operations (TAO) in both mission-critical and safety-critical applications [18]. The definition of CHMI^2 builds on and capitalises on significant developments in aerospace avionics human factors [83,84], which are detailed in Refs. [83, 84]. The CHMI^2 framework's primary feature is an expansion of a device monitoring approach that assesses a HMS entire integrity by including both cognitive (human) and automated (machine) components. It conceived to characterise the operator's actions that resulted in a certain mission outcome by detecting specific features that can affect cognitive states (for better or worse). This closed-loop input helps to improve the HMS trustworthiness in important areas like the initial design process. It supports cognitive system engineering activities, such as the creation of system automation methodology based on operator policies and online

Table 5
Levels of automation. From Ref. [76].

Level	Name	Description
1	Manual	Human performs all mission aspects
2	Tele-operation	Machine assists in task execution
3	Assisted Tele-operation	Machine assists in sensing and task execution and intervenes when needed
4	Advisory Execution	Human formulates mission and machine executes the task
5	Skilled Execution	Machine assists in sensing and planning and executes the task
6	Shared Control with Human Initiative	Autonomous Machine operations with human oversight
7	Shared Control with Machine Initiative	Autonomous Machine operations with human assistance
8	Supervisory Control	Autonomous Machine operations with a human directive
9	Executive Control	Autonomous Machine operations with human override
10	Full Autonomy	Autonomous Machine operations without human intervention

adaption of the HMS based on the cognitive state of the person and the operating environment, during the early design process [82].

The evolution that leads to introducing the CHMI^2 over the time is shown in Fig. 18. Similar to what has happened in the computer era, AI technology has enabled a new sort of CHMI^2 collaborative interaction that would eventually lead to a paradigmatic shift in CHMI^2 application areas in the AI era, resulting in new design thinking and approaches to AI system development. Subsequently, by using the human-machine co-operative relationship, it may be possible to optimise the benefits while limiting the potential safety risks of utilising AI technology.

4. AI techniques for space systems

The term "intelligent space system" refers to space systems that operate independently using intelligent methods. To achieve autonomy, AI approaches are used. Tasks are completed without the need for human interaction in this system. Not only can AI assist in physically speeding up the process of manufacturing satellites, but it can also be used to analyse the process to determine if there are any ways to enhance it. Furthermore, AI may examine previous work to make sure everything is completed correctly. Furthermore, including collaborative robots ("cobots") into the production process decreases the requirement for human workers in clean rooms. It improves the consistency of production processes that are prone to errors. AI, unlike humans, does not require rest or sleep in order to digest large amounts of data quickly. The basic objective of the techniques utilised can also be used to classify AI, resulting in the following four layers [65,73,86]:

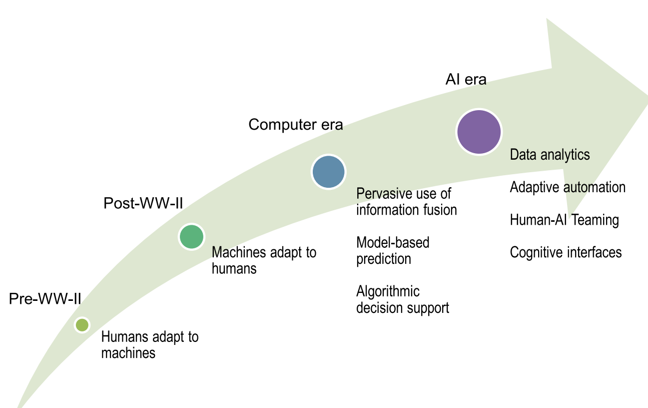

Fig. 18. The development of the human-machine relationship across time. Adapted from Ref. [75].

1. A foundational layer that covers traditional methodologies like statistics and econometrics, as well as complexity theory and game theory.
2. A behavioural layer that comprises operational procedures including automated processes, machine translation, as well as collaborative and adaptive systems, among others.
3. A sensory layer that provides language, audio and visual information to the model.
4. The "intelligence" is provided by a cognitive layer that incorporates ML, reasoning and information representation.

These definitions are helpful in thinking about the purpose of the strategies being used. A combination of these would be used for the most advanced AI systems.

4.1. AI techniques

AI, in contrast to natural intelligence, is the study of intelligence as manifested in computer systems and observed in people and other life forms [87]. To be considered intelligent, a computer system must be capable of making reasonable judgments based on experiences and observations of the world (or a simplified model of it) and a set of objectives to be met. By applying suitable AI techniques, satellite systems can make decisions in real-time without the need for explicit instructions. A plethora of studies coupled with many tests are underway to implement AI-based technology in space systems, with various projects beings carried out [71,73]. Some of the most commonly used AI methods are shown in Fig. 19. AI can also be classified into two distinct groups, strong AI and weak AI, based on the given task. Strong or general AI is concerned with the replication or outperformance of human brains, including sensitivity, consciousness, mind and feelings. Weak or applied AI, on the other hand, is focused on completing a single task or resolving a specific problem. Because most research in the space domain is limited to weak AI, this paper focuses only on applied AI.

4.1.1. Metaheuristics techniques

Most conventional optimization methodologies use a deterministic rule to switch from a single point in the decision hyperspace to another. The main disadvantage of this method is the local convergence limitation which may prevent reaching the global optimum. Since stochastic algorithms are designed to find the global best solution to problems with multiple local minima (usually nonconvex problems), they typically overcome this issue. There are two kinds of stochastic algorithms, namely heuristic and metaheuristic, though the distinction is minor. Stochastic optimization is sometimes the second-best way to get a solution. Conventional techniques such as linear programming, as well as specialised approaches that take full advantage of problem understanding, should be investigated first. Classical and specialised methods, on the other hand, are often naive, whereas heuristic and metaheuristic paradigms can be utilised to various conditions. One key advantage of heuristic and metaheuristic paradigms is their robustness. In this context, robustness refers to an algorithm's ability to solve a wide range of problems and even multiple sorts of problems, with only slight changes to account for each problem's specific properties. A stochastic algorithm typically requires the length of the problem-solution vectors, certain information about their encoding and an evaluation function, with the remainder of the programme, remaining unchanged. A heuristic algorithm is a strategy that uses a rule (or a set of rules) to find (or try to find) appropriate solutions at a low cost of computing. Theoretically, a heuristic provides (eventually) a decent answer with relatively little effort, but this does not ensure optimality. Heuristics are a straightforward way of showing which of many options appears to be the best [88,89]. The so-called metaheuristic algorithms are an extension of heuristic algorithms. Meta signifies "beyond" or "higher level," and metaheuristics outperform simple heuristics. Heuristics use problem-specific information to identify a "good enough" solution to a

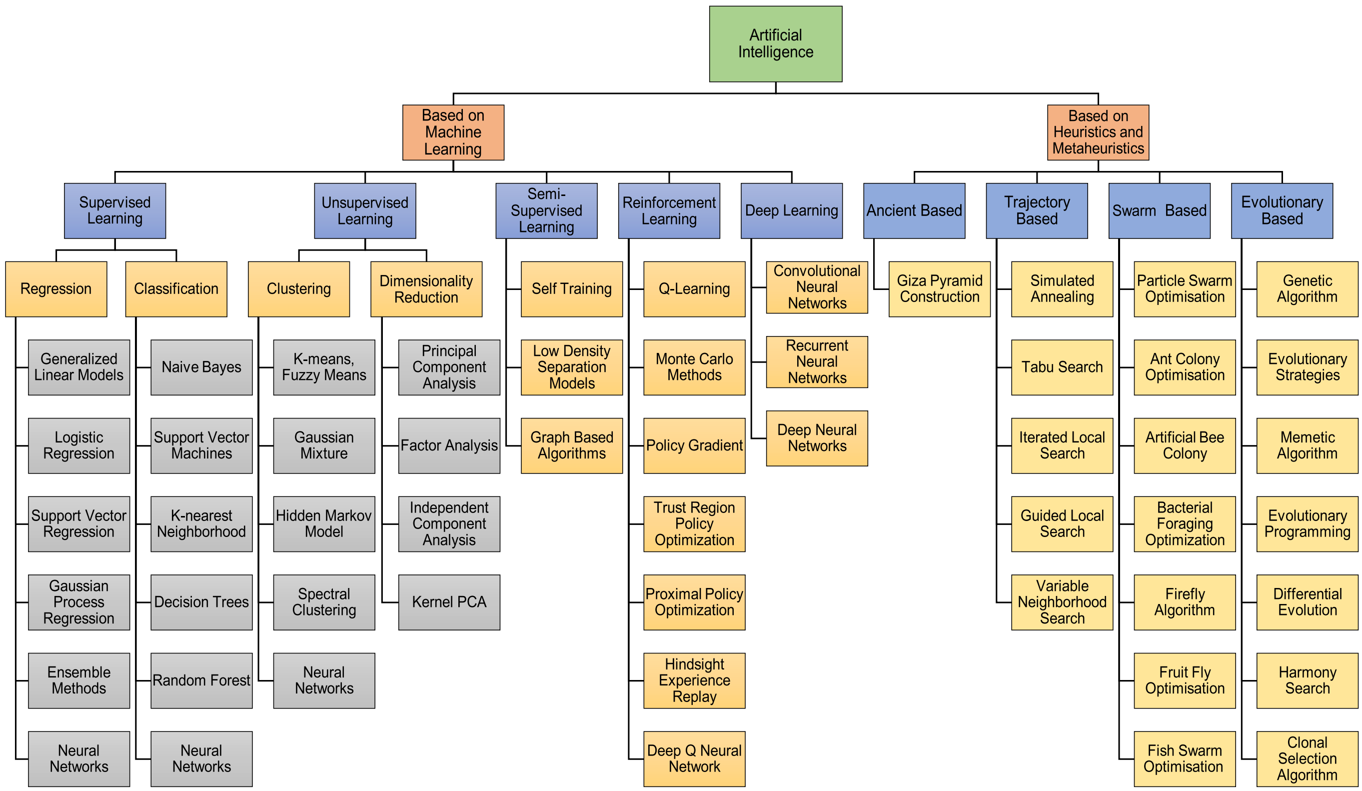

Fig. 19. Most common AI techniques suitable for space systems.

given problem, but metaheuristics, such as design patterns, are broad algorithmic notions that may be applied to a variety of problems. Importantly, all metaheuristic algorithms use some sort of randomization and a trade-off between local and global search. Practically every metaheuristic algorithm strives to be appropriate for global optimization [90]. The following features are shared by almost all metaheuristic algorithms [91]:

- They are nature-inspired, relying on physics, biology, or ethology principles;
- They use stochastic components (incorporating random variables);
- They do not use the objective function's gradient or Hessian matrix; And
- They have multiple parameters that must be adapted to the nature of the problem.

Metaheuristic optimization algorithms can solve complex problems over several iterations. Because of their inherent versatility and simplicity, metaheuristic algorithms have recently attracted a lot of attention. Metaheuristics can be broadly classified into four different types; the first one is ancient inspired, mainly based on the Giza pyramid construction. Mutation, reproduction, recombination and selection are the fundamental processes involved in evolutionary algorithms, which are based on the survival fitness of candidates in a population (i.e., a set of solutions) for a specific environment. The idea of population-based metaheuristics is to construct a solution that combines components of good solutions. Trajectory-based metaheuristics are based on the idea of developing a solution and iteratively refining it (moves). The reader is referred to Refs. [88–96] to get a complete understanding of these concepts. A population-based metaheuristics approach, i.e., nature-inspired, as indicated in Ref. [97] are, distinguished by:

- Their use of a population of points (potential solutions) in their search;
- Relying on direct fitness data rather than function derivatives or other similar details;
- Using probabilistic, rather than deterministic, transition rules.

Population-based algorithms adopt a similar approach, regardless of the applied paradigm and follow from the algorithm below.

1. Initialise the population;
2. Fitness is calculated for each individual in the population;
3. Produce a new population-based on some rules that strictly depend on the fitness of each individual;
4. Repeat steps 2–4 until a condition is met.

4.1.2. Machine learning techniques

ML approaches are a subset of AI techniques that allows for the creation of analytical models to be automated. It is a branch of AI based on the idea that computers can learn through data, identify patterns and make judgments with small or no human intervention. A ML process is shown in Fig. 20. A model that can be queried by an application is trained based on a data or knowledge base. Regardless of suitable conditioning, data selection, or overfitting, the model improves with a larger database and longer durations of training. If the model can learn in the field, the application can add data to the knowledge base during

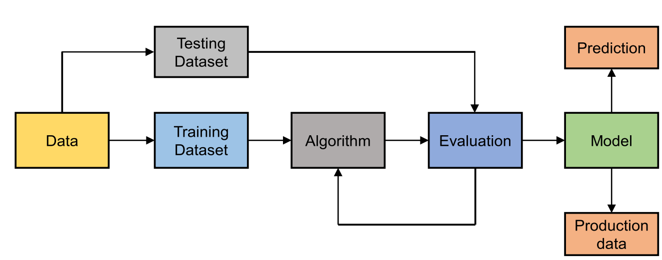

Fig. 20. Generalized machine learning process [98].

runtime and train the model with it.

A brief review of ML methods and an exposure to commonly used domain terms are provided in the preceding s sections. Different techniques for classifying ML methods have been taken in the literature. The most prevalent taxonomy in which techniques are classified according to the type of learning system used. The main variants of ML techniques are:

Supervised learning: the algorithm is supplied with labelled training data, i.e., appropriate labels are included in the desired result. During the training phase, a model is constructed that specifies the link between the training data points' features or characteristics and the labels that were allocated to them. The model would then be put to the test to see if it would generalise to new information points or 'incidents'. Before being deployed to service, trained models were fine-tuned based on the assessment findings to create a model that extrapolates well with the new data. In most supervised approaches, the learning method is to keep track of the difference between both the model prediction and the label and use it as an error term to drive model updating [3,81].

Unsupervised Learning: the training data provided to the algorithm is unlabelled and the relationship model is created solely on the data

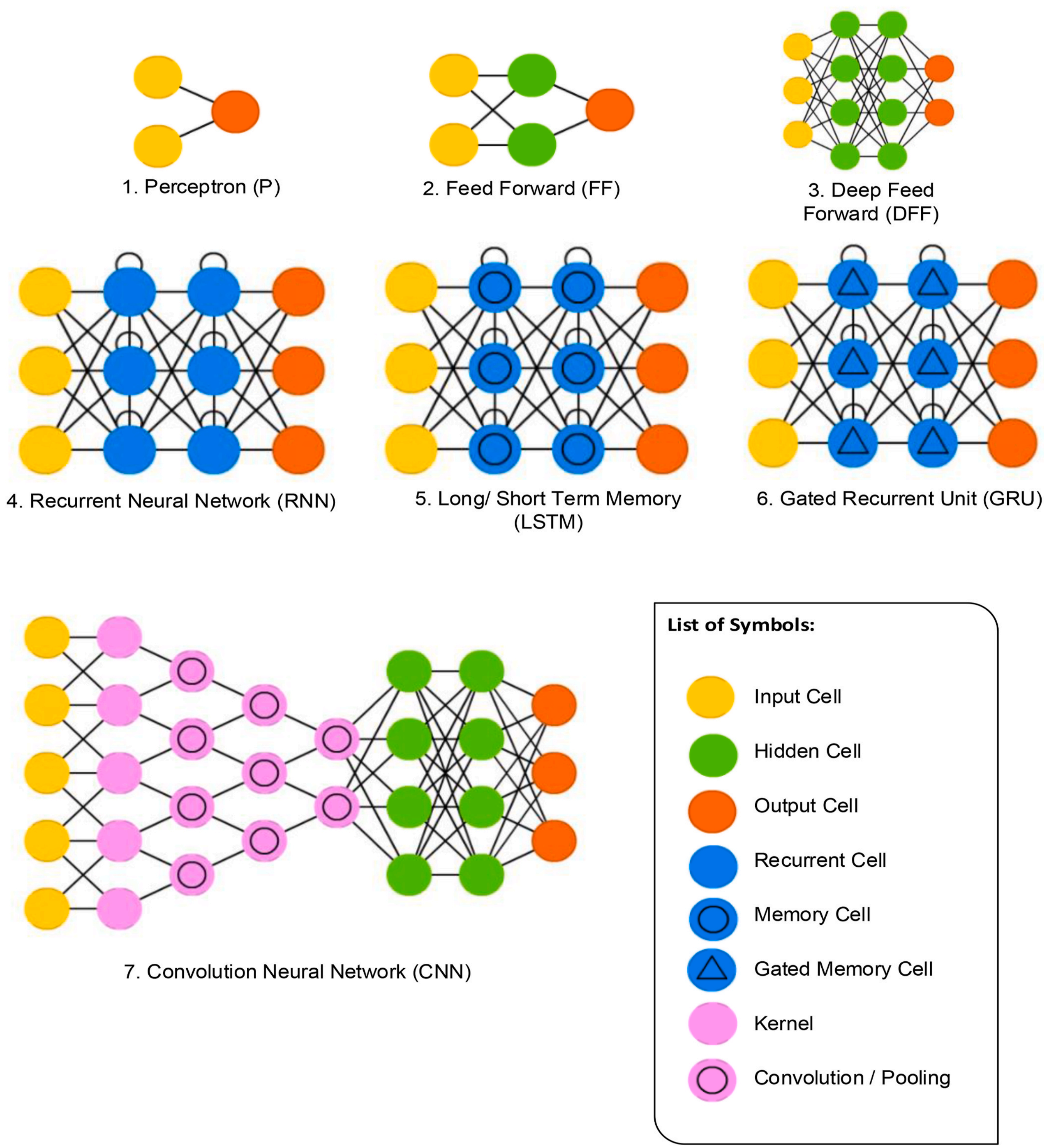

Fig. 21. Neural Network Categories [81].

attributes. These methods include clustering, dimensionality reduction approaches and association rule-learning methods [3,81].

Semi-supervised Learning: is a technique that involves training using a small amount of labelled data and a large amount of unlabelled data. Semi-supervised learning is a sort of learning that falls somewhere between unsupervised (in which there is no labelled training data) and supervised learning (with labelled training data) [81].

Reinforcement learning: a model is trained to iteratively learn a behavioural policy through a large number of simulations, which is called the training set. The agent learns how to attain a goal in an uncertain and potentially complex environment through trial and error. In Reinforcement Learning (RL), AI is presented with a game-like scenario. The machine uses the method of trial and error to find a solution to the problem at hand. AI gains either rewards or penalties for the acts it takes in persuading the system to perform the actions the programmer desires. Its aim is to increase the overall award. As a result, the AI agent learns to do the best set of actions or rules to achieve a user-defined reward function. To find the optimal system settings autonomously, sophisticated learning and decision-making functionalities must be adopted, for which ML algorithms offer several advantages [99].

Deep learning is a subset of ML that learns from data using artificial neural networks. Artificial Neural Networks (ANN) are based on the human brain and consist of layers of interconnected nodes. Each node in a Neural Network (NN) can learn to do something simple, like recognise edges in an image or identify patterns in text. By combining these simple tasks, neural networks can learn to execute complicated tasks such as object recognition in images and language translation. Deep learning (DL) is a powerful tool, but it must be used with caution. DL models are prone to bias and can be exploited to generate damaging or misleading resources. It is critical to be aware of these hazards and to take precautions to mitigate them. ANN is a type of AI that tries to replicate the way the human brain works. The processing units are ANN that are composed of inputs and outputs. ANN are a kind of ML technology that is inspired by biology and is supposed to work in way similar to the brain (loosely). Fig. 21 depicts the main types of NN types [3,81].

There are some distinctive attributes to be considered with specific reference to the adopted neuron model network, learning method and topology. Convolutional Neural Networks (CNN) are regularised versions of the multilayer perceptron. Such perceptron are typically fully connected networks, in which each neuron in one layer is connected to all neurons in the next layer [99]. CNN are generally used for segmentation, classification, image processing and other auto-correlated data processing. They are also utilised for speech recognition. Convolution is the process of applying a filter to an input signal as it is being played back. When looking for specific elements in a picture, it may be more productive to look at little sections of the image rather than the entire image at once. Among the most common applications of CNN is image classification, such as discriminating between satellite images that feature roadways and those that do not. The use of CNNs for other standard functions such as image segmentation and signal processing is also a good fit for them. Each layer of a CNN model learns a collection of convolutional kernels throughout the training operation, which is essentially what happens during the training phase. During the deployment of the model, the trained kernels extract spatial information. Each convolutional layer is made up of a collection of filters known as convolutional kernels, which work together to create the final result. Filtering is accomplished by applying a subset of the input pixel values to a matrix of integers that has the same dimensions as the kernel [100–103]. The CNN thus far seen are classic feed-forward networks, in which activations travel from the input to output layers at a predetermined rate. The network output is distinct from the outputs of previous timesteps at any given timestep. Recurrent Neural Networks (RNN), on the other hand, keep track of previous outputs at each epoch by integrating feedback loops. RNN are better at learning temporal relationships in data sequences than NN, which are meant to learn spatial patterns [81]. There is no sharp divide between these subtypes, even though the concepts seem to vary. In addition, they integrate within projects, as the models are structured to execute the task in the most efficient way possible, not to stick to a pure type. So, what distinguishes ML, DL and RL precisely is actually a difficult question to address, which can be addressed by following the standards shown in Fig. 22.

4.2. AI in space operations

The field of data-driven AI has a wealth of valuable and adaptable tools that can be used in various applications with minimal enhancements. While AI has been used successfully in space, it is still constrained to offline data processing but has not yet been utilised fully "on the edge" within spacecraft. Space Applications of AI has the potential to significantly affect human and robotic space exploration missions in several different ways.

As time progresses, AI will complement the space exploration activities in a variety of ways, as seen in Fig. 23. Some of the main applications of AI and intelligent systems in the near-Earth region and multi-planetary exploration in outer space are:

- Remote sensing data analytics.
- Satellite trajectory planning and collision avoidance.
- Satellite health monitoring.
- Satellite communications.
- Deep-space and multi-planetary exploration.

Table 6 gives a summary of AI techniques utilised in different spaceflight operational tasks.

4.2.1. AI for remote sensing data analytics

EO and astronomical satellites nowadays process about 150 gigabytes of observation data per day or more. The autonomous acquisition and processing of images introduces a number of opportunities where AI can assist greatly. Without AI, humans are largely responsible for interpreting, comprehending and analysing imagery [86]. By the time a human arrives around to evaluate an image, the satellite may have moved back to the same place, requiring more refinement of the image analysis. The AI-enabled recognition gives the researcher a lot of power when it comes to image analysis and reviewing the millions of images produced by satellites. On the other extreme, AI can analyse images as they can be captured and identify whether they have any anomalies [102,109,110]. The use of AI to process satellite images also eliminates

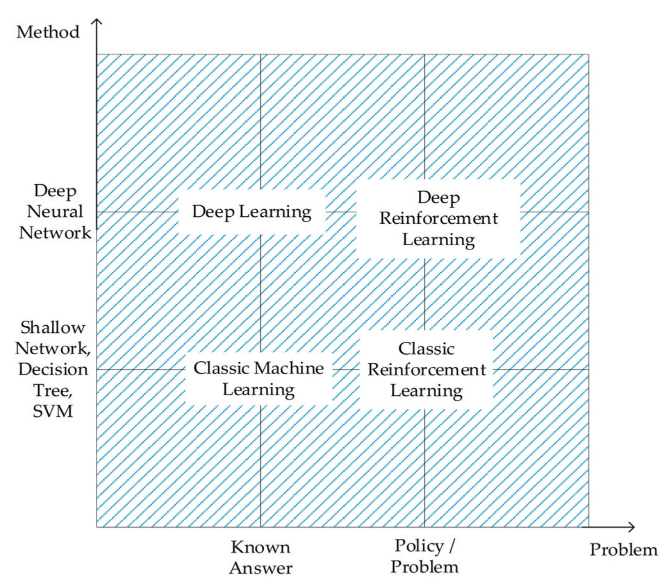

Fig. 22. Classification Standard [104].

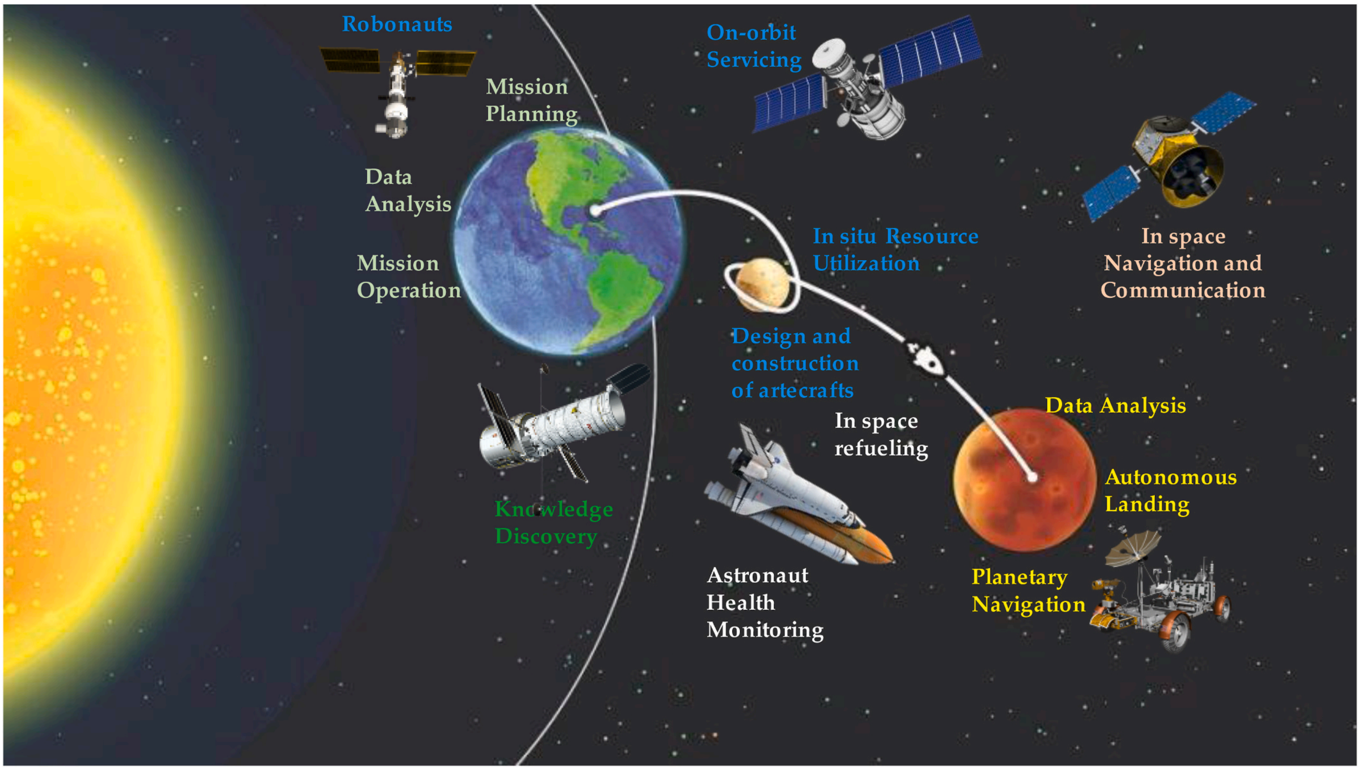

Fig. 23. AI-augmented space exploration.

Table 6
Summary of AI techniques used in spaceflight tasks.

Spaceflight Tasks	Techniques	References
Remote sensing	• On-board data processing • Image processing for precision agriculture and agroindustry • Hyperspectral image classification	[102,103,105–118]
Communication	• Satellite communication • Intersatellite communication • Space communications cognitive engine	[119–124]
Automated control and navigation.	• Satellite attitude control • Autonomous proximity operations and docking of spacecraft. • AI-based control systems	[125–133]
Satellite Health Monitoring	• Automatic anomaly detection techniques • Intelligent health monitoring systems • Spacecraft structural health monitoring	[134–140]
Deep space and Multi-Planetary Exploration	• Exoplanet detection • Interplanetary trajectory design • Deep space communication	[119,141–148]
Satellite Mission Planning	• Autonomous planning and scheduling • Trajectory optimization of the space launch vehicle • Spacecraft trajectory optimization	[15,133,149–155]
Space Traffic Management	• Collision avoidance • Separation assurance • Space Based Space Surveillance • Space domain awareness	[6,156–163]

the need for a lot of communication to and from Earth to analyse images and decide whether or not a new one should be acquired. AI therefore saves computing power and radiofrequency spectrum utilization by minimising communication, lowering battery use and accelerating the image collection process [109].

4.2.2. Satellite mission planning and collision avoidance using AI

Satellites are complex systems of systems and many issues could affect their operation, ranging from equipment malfunctions to crashes with other satellites/debris. AI can be used to maintain track of satellite health and ensure that it continues to function properly. AI can keep track of sensors and equipment in real-time, generating integrity flags (i.e., both predictive and reactive alerts) and, whenever appropriate, taking corrective action. AI can also be utilised to control satellite orbital parameters and to perform advanced navigation tasks (e.g., DSS relative navigation and formation flight). AI can also enhance the surveillance tasks, such as tracking of other spacecraft and debris. Once AI has inferred the state vector of tracked objects, orbital propagation can be accomplished to identify collision risks and, when necessary, to implement an optimal manoeuvre for collision avoidance [134,136,138,139,164,165].

4.2.3. Intelligent Health and Mission Management

Satellites have intricate subsystems and equipment that are required for operation. Malfunctions in this equipment have the potential to lead to several on-orbit failures, such as attitude control malfunctions, battery and solar-array failures [166]. Conventionally, satellite operations involve very simplistic on-board Fault Detection, Isolation and Recovery (FDIR), and fault diagnostics and prognostics carried out by human operators on the ground from telemetry data. This arrangement is resource-intensive and time-consuming, therefore inadequate for missions involving large and complex DSS. AI can address this challenge by monitoring the health of all satellite subsystems and providing advanced diagnosis and prognosis, including both predictive and reactive integrity features supporting TASO. Additionally, a properly developed AI system can reconfigure DSS resources to mitigate its impact, thereby implementing the so-called Intelligent Health and Mission Management (IHMM), which allows to drastically reduce the demand for human

Table 7
Summary of AI techniques and their specific function in different space missions and operations.

Mission/Operation		Type of AI	Specific Function (performed by AI)
Earth Observation (Satellite Image Analysis)		Machine Learning	Object detection and classification in satellite imagery [98,175,176]
			Land cover classification and mapping [177–179]
			Change detection for monitoring environmental dynamics [180–182]
			Anomaly detection for identifying environmental hazards [181,183–185]
		Computer Vision	Image segmentation, object detection [186,187]
		Data Mining	Detecting changes in Earth's gravity field, studying water resources [188–190]
		Neural Networks	Soil moisture mapping, drought monitoring [191–193]
		Deep Learning	Image classification and segmentation for land cover analysis [194–196]
			Change detection for monitoring environmental changes [197–200]
			Object detection and tracking in satellite imagery [201,202]
			Anomaly detection for identifying irregularities [203,204]
			Data fusion and integration for combining heterogeneous data [205–209]
			Super-resolution and image enhancement for improved analysis [202,210,211]
			Automated feature extraction for object identification [212,213]
			Data compression and transmission optimization [214–217]
			Data quality assessment for ensuring reliable data [218,219]
Space Debris Monitoring and Mitigation		Machine Learning	Object tracking and prediction of space debris movement [220,221]
			Collision prediction and avoidance maneuvers [222,223]
			Debris removal mission planning and optimization [224,225]
Astronomy		Machine Learning	Image classification, data processing [226,227]
		Neural Networks	Exoplanet detection, data analysis [148,228–230]
		Deep Learning	Star classification, astrometric measurements [231–234]
		Computer Vision	Image processing, object detection [235,236]
		Data Mining	Image reconstruction, black hole imaging [227,237,238]
		Pattern Recognition	Galaxy classification, dark matter detection [239,240]
Satellite Operation	Autonomous Navigation	Machine Learning	Trajectory optimization and path planning for spacecraft [241–243]
			Collision avoidance and space debris detection [222,223,244]
			Adaptive control systems for spacecraft maneuvering [245–247]
	Spacecraft Health Monitoring		Anomaly detection for identifying system failures [134,136,248,249]
			Predictive maintenance for optimizing maintenance schedules [167,250,251]
			Decision support for diagnosing and troubleshooting issues [134,136,167]
	Mission Planning and Scheduling	Optimization Algorithms	Resource allocation optimization considering mission objectives [252–255]
			Real-time adaptation and adjustment of mission plans [256–258]
	Communication	NLP Algorithms	Voice command recognition and spacecraft control [259–261]
			Intelligent responses and communication with astronauts [262,263]

involvement and is potentially much timelier and more effective in addressing anomalies [167]. After immediate automated mitigation and recovery measures, human operators can still implement offline investigation and forensics to obtain further information on newly discovered issues and resolve them. Since only non-nominal situations necessitate operator intervention, the "human-on-the-loop" concept is promoted. Increased on-board autonomy would allow for more complicated satellite applications missions, as well as reduce human operator workload [168].

4.2.4. *Satellite communications using AI*

It can be challenging to communicate between Earth and space, in addition to keeping spacecraft operational. Interference with other signals and the environment depends on the state of the atmosphere and on neighbouring entities. A satellite may have communication difficulties to overcome as a result of uncertainties in the environment. AI is now being utilised to control satellite communication in order to circumvent any transmission issues. These AI-enabled technologies can figure out how much power and what frequencies are needed to send data back to Earth or to other satellites. The satellite does this on a regular basis with an on-board AI to allow signals to pass through as it travels through space [169–173]. In particular, AI can greatly support several communication system tasks, including beam-hopping, anti-jamming, detecting ionospheric scintillation, network traffic forecasting, channel modelling, telemetry mining, interference management, remote sensing, behaviour modelling, space air-ground integrating and energy management. AI should be used to produce more effective, reliable, consistent and high-quality communication systems in the future [122].

4.2.5. *AI for deep space and multi-planetary exploration*

Even satellites on other planets or in interplanetary space, like the Curiosity rover currently on the red planet, use AI to operate. The Mars rover is using AI to assist it in navigating the planet. The computer may make several modifications to the rover's trajectory every minute. The Mars rover's technology is quite similar to that used by self-driving automobiles. The key difference is that the rover should cross more difficult terrain without having to worry about other vehicles or pedestrians. The rover's computer vision systems analyse the difficult terrain as it traverses. If an issue with the terrain is detected, the autonomous system adjusts the rover's navigation or modifies its trajectory to avoid it [22,71,142–144,174]. A summary of AI techniques and their specific function in space missions and operations is presented in Table 7.

4.3. *On-board AI*

Currently, AI is employed in space to improve monitoring and diagnostics, make predictions and analyse images. AI has not yet been implemented on-board spacecraft. Image processing, instrument control and satellite navigation are just a few of the potential applications for AI on-board spacecraft. Training models on the ground and then uploading them to spacecraft is one method to implement AI on-board of the spacecraft. This would make spacecraft more autonomous and increase the value of the data they collect. Even the most computationally demanding AI models can now be executed on mobile devices such as smartphones. This indicates that AI can be utilised on even the smallest spacecraft. Table 8 provides examples of specific AI applications on on-board of the spacecraft. Space exploration has the potential to be

Table 8
A brief overview of AI on-board missions. Adapted from Refs. [264,265].

Mission	Specific Function (performed by AI)
In-orbit servicing: Debris removal, Docking,	i.Feature extraction ii.Identification against 3D mesh model iii.Obstacle avoidance
EO missions (to be scaled to mission size, criticality, duration)	i.Band co-registration for push-broom multispectral and hyperspectral images ii.Change detection in time series of Earth Observation images, various resolutions iii.Cloud detection algorithms (F-mask or Sen2Cor, however, the whole Sen2Cor is quite big, maybe some essential parts of it) iv.Fire/flares detection v.Image compression (jpeg/CCSDS), (preferably Earth Observation-like picture) vi.Increase resolution of all Sentinel-2 bands to 10 m/pixel vii.Monitoring of forest distribution viii.Monitoring of ice at poles ix.Open sea objects detection and monitoring x.Reconstruction involving multiple Images alignment using SURF equivalent, like BRISK or ORB (SURF is patented) and RANSAC xi.Super-resolution (increase resolution using series of images) through compressive sensing methods, like over-determined equations xii.Supervised NN Image Classification of Multi-Spectral Images Based on Statistical Machine Learning (TBD if learning speed should be measured as the benchmark as well) xiii.Template matching (scale and rotation invariant) in Earth Observation-type image (e.g., from Sentinel-2) xiv.Vessel detection/identification, integration and data fusion with AIS receivers - identification of piracy
Visible spectrum EO mission (For generic Imaging Instrument calibration)	i.Active/adaptive optics: wave front analysis + actuation ii.Auto-exposure iii.Flat field dynamic correction iv.Focal plane adjustment and calibration v.Geometric calibration vi.Top of Atmosphere calibration
Visible spectrum astronomy (For on board platform imagers processing)	i.On-board platform imagers processing ii.Identification of fast-moving meteoroids/disturbance/radiation iii.Star tracing and multiple sensor data fusion iv.Orbital propagation
Planetary Exploration	i.Camera/LIDAR fusion processing. ii.Identification of craters, boulders, obstacle avoidance, automatic path discovery iii.Vehicle GNC iv.Autonomous Landing v.Robotic Exploration
Reconfigurable platforms/on-board telemetry analysis, FDIR	i.Adapt platforms to change in requirements or new standards ii.Autonomous failure prognostic and detection iii.Autonomous Safe mode management. iv.AI-based FDIR
Satellite guidance applications	i.Autonomous AOCS management for constellations ii.Autonomous collision avoidance iii.Autonomous navigation iv.Autonomous pointing and/or acquisition (AOCS-in-the-loop) v.Payload-in-the-loop visual-based navigation vi.SDR/Beamforming/Adaptive Coding and Modulation vii.Smart FDIR/failure prediction/smart HKTM
New missions that are candidates for the use of AI	i.Reconfigurable science (several missions with the same Hardware/Instrument) ii.Servicing/Non-cooperative approach and rendezvous iii.Debris detection and removal iv.On-board feature extraction/mapping Raw data downlink only On-Demand basis or Added-Value basis v.Rapid alert: fire, flood, earthquake detection

revolutionised by AI. By incorporating AI into spacecraft, scientists can collect more data, make better judgements and conduct space exploration in a safer manner [264,265].

5. Space infrastructure evolution

The benefits offered by AI algorithms will be fully achieved upon integration in all space mission operational segments (Fig. 24): space, control, user, link segments and inter-vehicle communications.

5.1. Space and control segments

The space segment involves a variety of specialised payloads, such as remote sensing, navigation and communications, to carry out the intended missions [21]. In addition to other more mission-specific aspects extensively covered in other sections of this article, spaceborne systems are increasingly relying upon suitable forms of AI to autonomously check for faults, detect/isolate them and recover optimal functionality [266–269]. Concerning the control segment, various functions are seeing an increasing adoption of AI [270–273]. Ground control systems, in particular, is being extensively automated to reduce the reliance on human operators and associated support personnel [268,269,274,275]. These systems can handle numerous spacecraft at the same time, normally requiring minimal human supervision and intervention. For example, NASA's Near-Earth Network and Space Network use time-sharing to manage many spacecraft connections [276,277].

Table 9 summarizes the applications of AI envisaged for the evolutionary space and ground segments.

On-board control functionalities, have recently been the focus of increasing levels of automation, as in the case of system health management, which evolved from traditional FDIR practices. The capability to adapt and maintain dynamic plans for individual spacecraft prompts the adoption of on-board autonomy for both mission planning and execution [279]. Nowadays, most satellite operators/owners prefer on-board control due to the limitation in bandwidth and the ability to perform autonomous operations [105–108]. These on-board control systems are able to process mission and link segment data such as EO data [271], space weather data, etc. without human intervention and employing intelligent algorithms. Table 10 summarizes the complementary nature of ground and space control segment components.

5.2. Inter-vehicle communications

The term Inter-Vehicular Communication (IVC) refers to data exchange within the DSS framework which can be achieved with ISL. The different topologies are shown in Fig. 25.

Mission tasks, including redundancy of operations, command and control, mission activities, tracking, networking of computing capabilities and communications, are all performed when functioning satellites connect with one another. As a result, the authenticity and integrity of these communications are critical. Space Traffic Management (STM), efficient and easier maintenance, are all benefits of vehicular communication, which ultimately lead to safer space operations. Wireless and optical fibre communications are the most common forms of IVC [275]. Different ISL topologies are the following 1) Ring, 2) Star, 3) Mesh, or 4) Hybrid, depending on the communication links between the DSS. These topologies are depicted in Fig. 25, with the ISL represented by the arrows. Liz Martinez et al. provides the various strategies that are suited for DSS [211]. Technology based on RF, has traditionally been utilised for inter-satellite communication; however, increasingly, modern satellites are turning to technology based on lasers and optics in order to communicate with one another [281–283]. Fig. 26 illustrates the different links between space and ground assets, which can support command and control functionalities such as initiate equipment diagnostics, reset the state of equipment, and/or begin the vehicle's propulsion systems. These commands can be transmitted to a space vehicle via a variety of communication mechanisms. For instance, they can be sent by optical fibre to a remote ground station, where they are sent to the satellite through a direct Radio Frequency (RF) or optical link. Alternatively, a space relay system can be established, in which initial commands are communicated from the ground through RF or optical to a relaying satellite, which will then be transmitted via radio frequency to the target satellite. Finally, mobile devices and technologies that are not tied to a specific ground operation region, like IVC, can be used to send commands to a satellite or its payload [275].

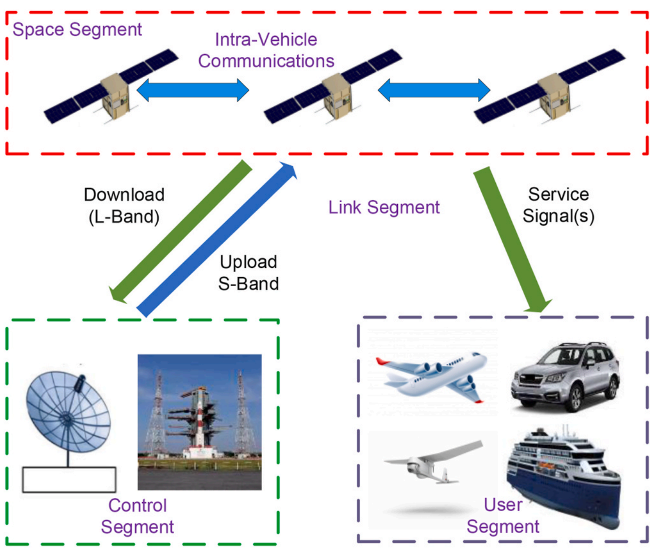

Fig. 24. Example of modern satellite system operational segments.

Table 9
AI application in space and ground segments. Adapted from Ref. [278].

Space segment application	Smart Payloads	• Ground target analysis segmentation, detection and tracking •Cloud segmentation •Vegetation detection and health monitoring •Multispectral and Hyperspectral information extraction
	Smart Spacecraft	•Automated planning and reasoning •Adaptive on-board operations •Event-driven and goal-driven autonomy •Autonomous Moon/Mars/Asteroid landing
Ground segment applications	Trend Analysis	•Anomaly detection on multivariate time-series •Intelligent health and mission management •Correlation on multivariate time-series •Automated root cause analysis
	Augmented Operations	•Satellite automated tasking and planning •Automated debris avoidance •Virtual assistants for ground operators
	Generative AI	•Dataset augmentation •Super-resolution imaging •Data quality enhancement

5.3. User segment

The user segment includes civil and military equipment that receives and processes satellite signals. Specialised receivers and/or transceivers are required in most applications such as communication, navigation, positioning, time dissemination and research (such as measurement of atmospheric parameters). As the term suggests, receivers have no restriction on the number of users they may serve because the signals are sent in the service volume to each suitable receiver, making communication one-way, meaning the user does not broadcast but only receives. The variety of transport, surveying, agricultural, industrial, defence and recreational applications currently found for Global Navigation Satellite Systems (GNSS) receivers, has created a large and diverse user community base. Today, most mobile and personal communication devices feature embedded GNSS receivers, with an increasing number of applications depending on satellite navigation signals. The aviation community strongly supports GNSS evolutions because they provide dependable aircraft's positioning and navigation [284,285]. Satellite communication services are also increasingly more accessible and extensively used for beyond Line-of-Sight (BLOS) aeronautical communication networks, including those serving uninhabited/autonomous air and surface vehicles. Other common applications include Earth Observation (EO), where service owners/users access various kind of raw, semi-processed and processed datasets including weather, agricultural, geospatial, etc. [286–288].

Table 10
Comparison of ground and space control segment. Adapted from Ref. [279].

Ground Control	On-board Control
•CPU power available, •Software flexibility, •The testing procedure not impacting the mission, •Interactions with operators and experts in a short loop, •Lower cost of software development.	•Reactive to the environment, •Processing data without communication delay, •Reduced communication to ground, •Human intervention is limited.

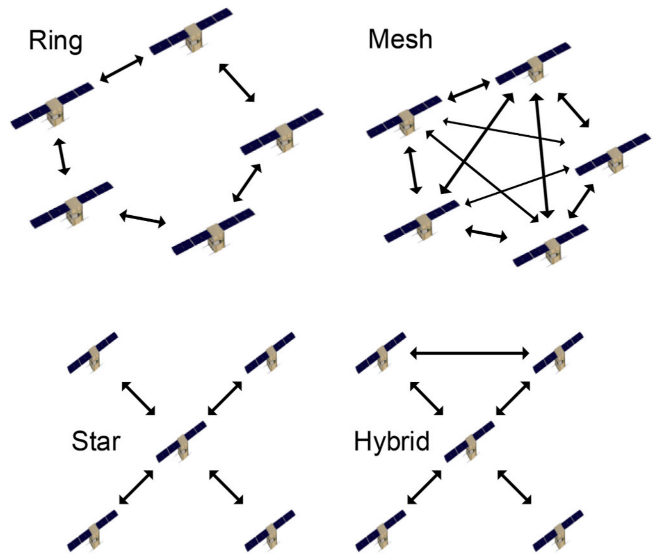

Fig. 25. Different ISL topologies [280].

5.4. Co-evolution of space and control segments

Trusted autonomy is envisioned to increase efficiency and cost-effectiveness in both space and control segments, especially by lowering the significant recurring costs of operating space missions. The increasing amounts of data processing and interpretation performed within the space segment will lead to less raw data downlinked and process on the ground, thereby reducing the requirements for spectrum, human operators and ground-based computational resources. By automating the processing and interpretation of operational information from different sources, the technical expenses of operating a spacecraft and responding to anomalies can be lowered [71,106,108]. Increasing the level of autonomy within the space segment is therefore critically important [71]. However, autonomous data analysis and mission planning decisions taken on-board can challenge the human understanding and situation awareness to a point where even a supervisory role would be completely compromised. A co-evolution of space and ground control segments is therefore necessary to allow a safe adoption of on-board autonomy and thus achieve trusted autonomy [6]. Contemporary research in human factors engineering is investigating how to evolve Human-Machine Interfaces and Interactions (HMI^2) in a way which best matches the complementary human and machine capabilities but also considering the ever-changing performance of both. This variability in space and time calls for adaptive and cognitive forms of HMI^2, which can maximise human situation awareness and correct interpretation of a variety of situations in a supervisory (human-on-the-loop) control paradigm. It is increasingly evident that AI can be a critical asset in both segments to endow the overall CPH system with the necessary cognitive adaptation capabilities and therefore achieve trusted autonomy [85,289]. The heuristic and unpredictable character of some operational decisions aboard spacecraft and the difficulty of algorithmically encoding elements such as expert judgment in such systems create considerable challenges on this front [143,268,269]. Hence the co-evolution of these two segments will be essential to enable TASO. Fig. 27 depicts a possible approach to address the challenges of space and control segment co-evolution. In particular, the proposed architecture supports autonomous goal-based mission planning based on both SBSS data and ground-based surveillance data from the Consultative Committee for Space Data Systems (CCSDS), [6].

The accessibility of the information necessary to make actions is a critical consideration. The availability of such data should then define the chosen paradigm. For example, on-board autonomy is the obvious option if the goal is to make the system more resilient to failure, but if the intent is to maximise the system responsiveness to user requests,

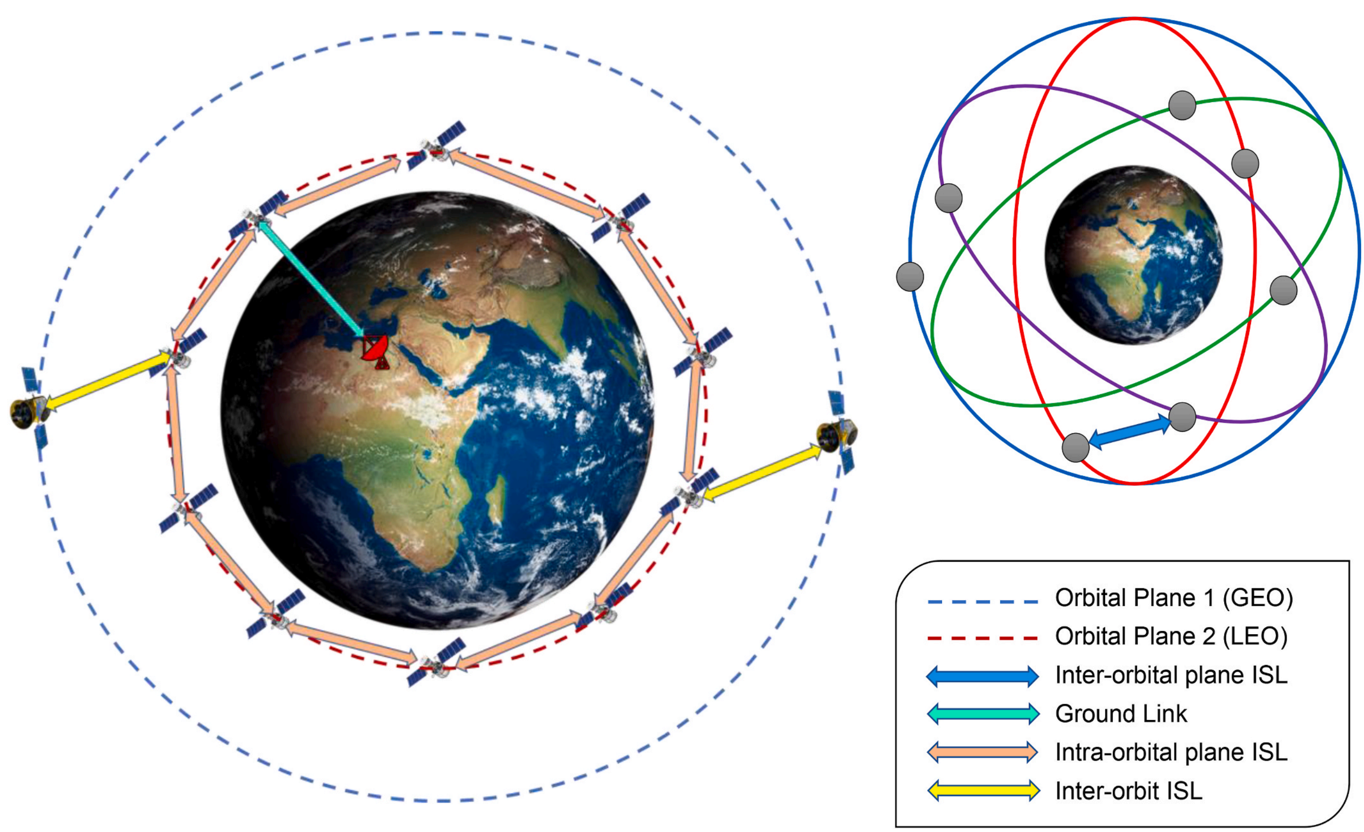

Fig. 26. Links between spacecraft and ground segment.

more complexity should be handled by the ground segment. Both options are generally required; hence, autonomy must be flexibly managed by either control or the space segment with variable levels of autonomy and associated task redistribution. Distributed mission scenarios may not always be adaptive to single spacecraft solutions. This is the case because distributed missions introduce a new level of complexity to mission planning, such as the spacecraft coordination mechanism. This is completely dependent on IVC and computing power, which are both finite resources. Determining the right degree of responsibility between both the control and space parts is one of the primary difficulties for future missions [279]. Ultimately, even goal-based operational concepts alone cannot address the requirements of trusted autonomy without resorting to cognitive/adaptive forms of HMI^2 such as the $CHMI^2$ concept overviewed in

section 3.1.2.

5.5. Intelligent DSS operations

On-board data processing (i.e., reducing data link load and relaxing ground-based processing tasks) requires both AI algorithms (software) and suitable hardware (such as accelerators). TASO is therefore possible only with cutting-edge AI enabled astrionics. Astrionics are generally subdivided in two categories: (i) *Service astrionics,* which includes on-board GNC, communication, mission reconfiguration, etc.; and (ii) *Mission astrionics*, which deals with mission-specific satellite-related tasks such as fusion, analysis, georeferencing and other data-related tasks. Sharing information about the acquired data is made possible by iDSS, allowing for maximum scientific output to be achieved through the use of opportunistic research. iDSS also offer real-time event management i.e., disaster and rare events. The operational requirements can be lowered with iDSS autonomy, allowing for human-in-the-loop operations to be converted into human-on-the-loop activities. Humans will be responsible for overseeing the operations in some capacity. Despite the loss of one spacecraft, intelligent DSS (iDSS) is able to continue working at normal levels and its trusted autonomous reconfiguration capabilities allow it to redistribute workload without interference from the ground. Therefore, iDSS enables real-time or near-real-time operations for time-critical events such as natural disasters (in this case, wildfires). In this context, ISL allows for data sharing and reactive AI algorithms perform on-board data processing so that the iDSS can reconfigure rapidly [290,291].

6. Current and future applications

The following subsections examine relevant use cases of AI in space operations. These examples illustrate the significant potential of AI to enhance a variety of real-world space operations. From autonomous satellite control to on-board data processing, AI has proved to be a potent tool for improving the efficiency, dependability and safety of space missions. These e demonstrate the potential for AI to revolutionise space operations and bring us closer to understanding the complexities of the Earth and deep space.

6.1. PhiSat-1 mission

The European satellite PhiSat-1 (φ-Sat-1) is the first to demonstrate how on-board AI might improve the efficiency of EO data transmission back to Earth. Enhanced imaging capabilities employing a hyperspectral camera and HyperScout-1 imager, as well as advancements in a Federated Satellite System (FSSCat) mission using AI, have resulted in PhiSat-1. The presentation of a cutting-edge AI accelerator, including the first AI algorithms for cloud screening, was the highlight of the show. Applying ML algorithms to HyperScout-2 data in real-time allows for considerable improvements in inferring and presenting EO-based information at high temporal precision and in a short amount of time. Scanning data before it has been downloaded is one possible use case. This was the case in the first experiment, which took place in orbit as part of the φ-Sat-1 mission and involved AI being utilised to retrieve

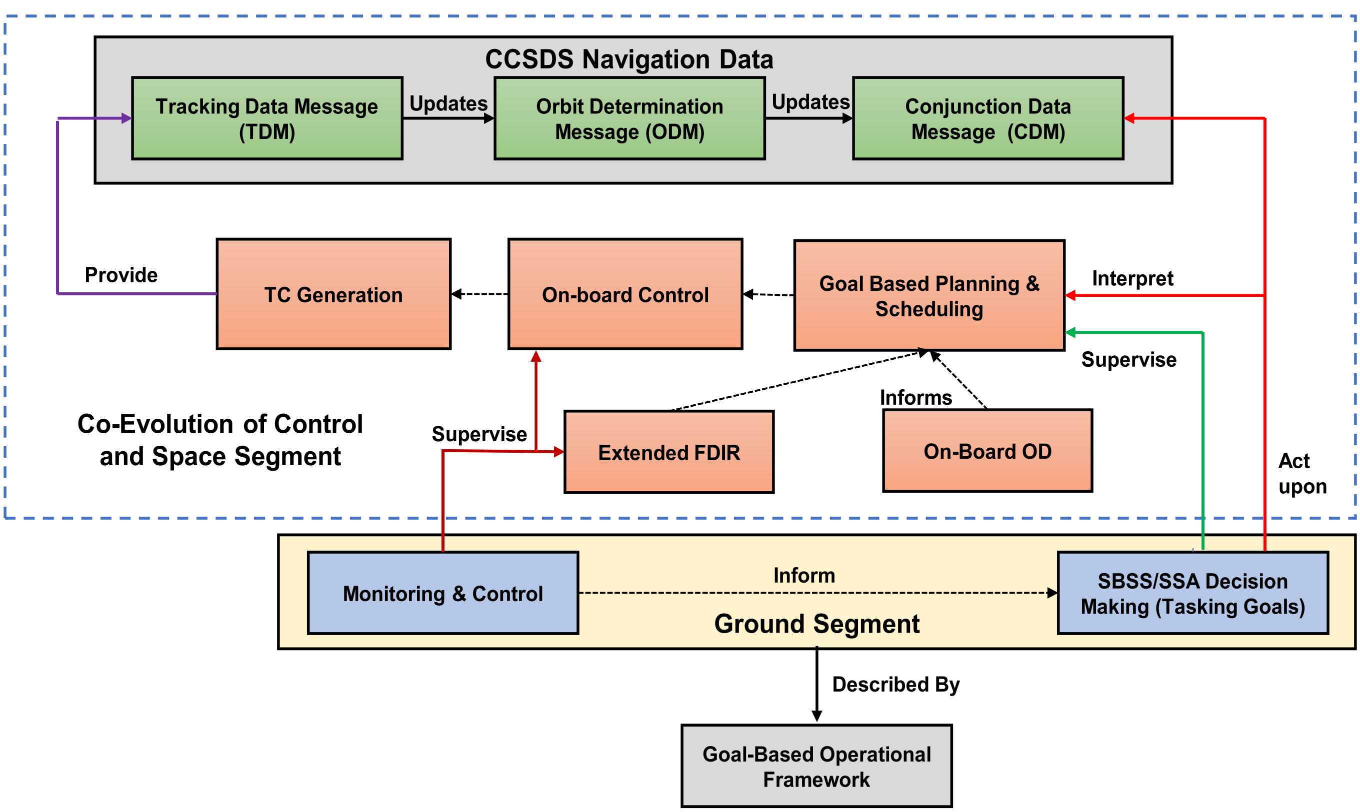

Fig. 27. Concept of space and control segment co-evolution by goal-based programming. Adapted from Ref. [6].

cloud coverage data from the gathered picture [272].

6.2. Disaster management

Climate action (SDG-13) is one of the United Nations (UN) Sustainable Development Goals and wildfire is one of the catastrophic phenomena that both impact and are exacerbated by climate change. Large-scale wildfires have increased in frequency and size in Australia and other nations in recent years. The capacity to change the spacecraft cluster/formation and progressively add new or upgrade existing satellites in the formation has surely increased mission value in recent improvements in DSS. These qualities have intrinsic advantages such as greater mission efficacy, multi-mission capability, design flexibility and so on. The predictive and reactive integrity characteristics given by AI, including both on-board satellites and in the ground control segments, make TASO practical. The DSS must be able to reconfigure independently in order to efficiently monitor and manage time-critical events such as disaster relief operations. To achieve TASO, the DSS architecture should support reconfiguration and spacecraft should communicate with one another via an ISL. Recent breakthroughs in AI, sensor and computing technologies have created new promising concepts for the DSS's safe and efficient functioning. Combining these technologies enables trusted autonomy in iDSS operations, providing a more responsive and resilient approach to Space Mission Management (SMM) data collecting and processing, particularly when using cutting-edge optical sensors. This study investigates the potential uses of iDSS by proposing a network of LEO satellites for near-real-time wildfire management. Satellite missions must have sizable coverage, return intervals and reconfiguration capabilities to continually monitor Areas of Interest (AOI) in a dynamically changing environment, which iDSS can provide. Our recent works established the viability of AI-based data processing employing cutting-edge on-board astrionics hardware accelerators [292]. Based on these first findings, AI-based software for wildfire detection on iDSS satellites has been developed in stages. To show the applicability of the proposed iDSS architecture, simulation case studies in various geographic regions have been carried out and substantiate the viability of this mission concept [290,291,293–295].

6.3. Maritime ISR

In the twenty-first century, space based EO systems have undergone continuous development. Their application across the world's waterways, among others, has risen significantly with the help of space-based Maritime Domain Awareness (MDA), particularly Automatic Identification Systems (AIS). This study investigates the possible utility of Synthetic Aperture Radar (SAR) and DSS for MDA operations. A resilient multi-baseline Along-Track Interferometric Synthetic Aperture Radar (AT-InSAR) formation flying concept is developed to efficiently combine many along-track baseline observations for single-pass interferometry. The simulation findings show that it is possible to implement this acquisition mode with autonomous orbit control utilising low-thrust actuation appropriate for electric propulsion. A constellation of these formation concept is also proposed to improve repeatability and incorporate the benefits of the DSS. An MDA application is a hypothetical mission that will be solved using this integrated technique [296,297].

6.4. Mission management

Consistently with the IHMM concept, to facilitate trusted autonomous space mission management, the operational tasks to be performed and their schedule shall be defined and updated using suitable AI planning techniques that consider data collected throughout the mission (telemetry payload and external data). The satellites become aware of their environment, their health and the Mission Control Centre's eventual directives. During a mission, AI provides trusted autonomous decisions customised to the demands of end-users. The true, long-term benefit of a fully trustworthy autonomous mission is lower operational costs. This is especially relevant for small satellite missions, where costs of operations have been shown not to scale with spacecraft size and constellations, where a large number of operators for each spacecraft simply cannot be afforded with hundreds of thousands of satellites. At Technology Readiness Levels (TRL) 4 to 6, there are few mission management technologies available in the industry, MIRAGE [278] and Antelope [298] are the notable ones.

6.5. Space Based Space Surveillance

The effectiveness of space object surveillance in the rapidly evolving space domain is challenged on multiple fronts and is particularly known to be limited in the size and optical magnitude of the objects being monitored. Additionally, ground-based observations are prone to disruption and disturbance by atmospheric weather effects. SBSS is therefore widely considered as the long-term complement to ground-based RSO tracking as it is not affected by atmospheric weather and is able to detect much smaller and fainter objects. The integration of SBSS has the potential to enhance tracking accuracy, RSO predictability and weather independence, thus potentially supporting the development of an integrated Space Domain Awareness (SDA) framework for safe, sustainable and unrestricted LEO operations.

iDSS characteristics offer a lot of potential for SBSS missions as the number of observations and RSO potentially tracked make the downlink of data and a ground-based mission planning highly impractical. Lagona et al. [299] proposed AI algorithms for autonomous planning and reconfiguration onboard a SBSS DSS. For on-board trajectory generation, the proposed approach provided a viable autonomous manoeuvre planning solution employing PSO requiring common computing power. Because of the exceptional parallelization, robustness and efficiency features of PSO-based methodologies, high accuracy results were obtained within acceptable calculation timeframes for the desired SBSS mission. The suggested trajectory optimization methodology not only enables timely and responsive manoeuvring to support next-generation DSS missions, but it also provides a rationale for ground control segment progression towards trusted autonomous space operations. Despite these obvious advantages, metaheuristic solutions are stochastic in nature, posing a barrier to the interpretability and explainability of the computed manoeuvre from the standpoint of the human operator. The long-term goal of this research is to achieve a flexible and scalable RSO detection, SDA and collision avoidance capability. A strategy to extend the concept to cooperative tracking was proposed aimed at accurately measuring and estimating the kinematic states of RSO [300–303]. These studies examined an intruder (debris) being monitored by multiple space-based assets in this circumstance. For collision avoidance and separation assurance, the effects of manoeuvring the satellite to an appropriate level can be achieved by either performing an orbit raising or lowering operations [299]. The ultimate goal is to introduce a Space Traffic Management (STM) framework that complements conventional Air Traffic Management (ATM) in ensuring safe and efficient near-Earth space operations, including rocket launch/re-entry, satellite orbital deployment and manoeuvring, as well as new forms of point-to-point suborbital and orbital transportation [304,305].

7. Safety and security considerations

Since space assets provide their operators a significant strategic and technological advantage; an adversary will almost certainly aim to degrade, deny, or disrupt access to space system capabilities [306]. Fig. 28 depicts a list of the most common hazards/threats, along with the severity of each. Although cyberattacks are reversible to some extent in outer space, the TASO in space requires cyber resilience against cyber threats. Cybersecurity must be considered early in the design process, particularly in the context of TASO in iDSS. In the event of planetary threats such as debris or satellites, for example, autonomous orbit replanning is required.

7.1. Cyber-space

Cyber-space is the notional environment in which computer networks interact. The Fourth Industrial Revolution of the twenty-first century, propelled by the rapid and disruptive rapid rise of DL and ramped up by the synergy of cyberspace and AI, has assumed critical importance in modern defence and security [307–310]. Cyberspace is a complex hierarchical structure of interconnected technological and semantic layers (physical, logical, information and human). Humans use increasing amounts of information in their daily lives, thereby making it one of the most important resources nowadays. Satellites have historically benefited from “security by obscurity,” which prevents all but the most sophisticated cyber-attackers due to the system’s complexity and expensive equipment costs. Due to the widespread use of COTS components and constellations with thousands of identical satellites, operational complexity and diversity are unlikely to provide long-term security [311]. The danger to satellites is generally acknowledged and obvious. Space systems play a significant role in military C4ISR (Command, Control, Communications, Computer, Intelligence, Surveillance and Reconnaissance) capabilities [312]. In theory, competitors with strong motivations to “level the playing field” with big powers, are increasingly motivated to target satellites [313]. Public participation is dependent on space services, whether it be positioning information for everyday logistics and transportation or meteorological systems that protect millions from disasters. As a “single point of failure” in vital infrastructures, satellites may appeal to individuals who are looking to upend civilisation [314]. Cyber-threats exist in cyberspace, which must be taken into account and handled during all design, implementation and operational phases. Extra caution and system resiliency should be employed to reduce cyber dangers by implementing intelligent agents for TASO [18,315,316]. The framework for cybersecurity is shown in Fig. 29.

The framework is based on a customizable cybersecurity risk management approach for different industries. It establishes a common terminology and methodology that organisations can use in line with their available resources and operational needs. Five functions make up the Cybersecurity Framework: identify, protect, detect, respond and recover. To emphasise to users that cybersecurity is an active process that enables a company to navigate the constantly evolving spectrum of cybersecurity threats, the functions are represented in a circular pattern [275,317].

7.1.1. Inter-vehicle cybersecurity

The ability of the satellite vehicle to protect itself from cyberthreats, recognise threat actions, respond to cyberattacks, and, if required, recover is referred to as inter-vehicle cybersecurity. These capabilities have to be included in the cybersecurity development cycle and applied early in the life cycle of the iDSS system. Small commercial satellite owners and operators are frequently responsible for inter-vehicle cybersecurity, while the majority of the remaining infrastructure is contracted to certain other suppliers and providers [275].

7.2. Satellite resilience

The aerospace industry of an increasingly multi-polar world will have to negotiate a future that is getting more and more crowded with familiar, unfamiliar and unfriendly players all vying for technological and strategic superiority. Threats to the space realm and its sustaining infrastructure have escalated as a result of this change [318]. Ground and aerospace system architectures must offer a high level of resilience in order to ensure mission success. Resilience is therefore a crucial design factor that should be traded off against cost and capabilities when making decisions [319]. States now recognise their reliance on space-based services due to their growing significance for military activities. For these reasons, the majority of governments consider any operation to have space support. However, few individuals legitimately comprehend its contribution, let alone the effects of any space service suspension or significant degradation [306,307,319–321]. A taxonomy

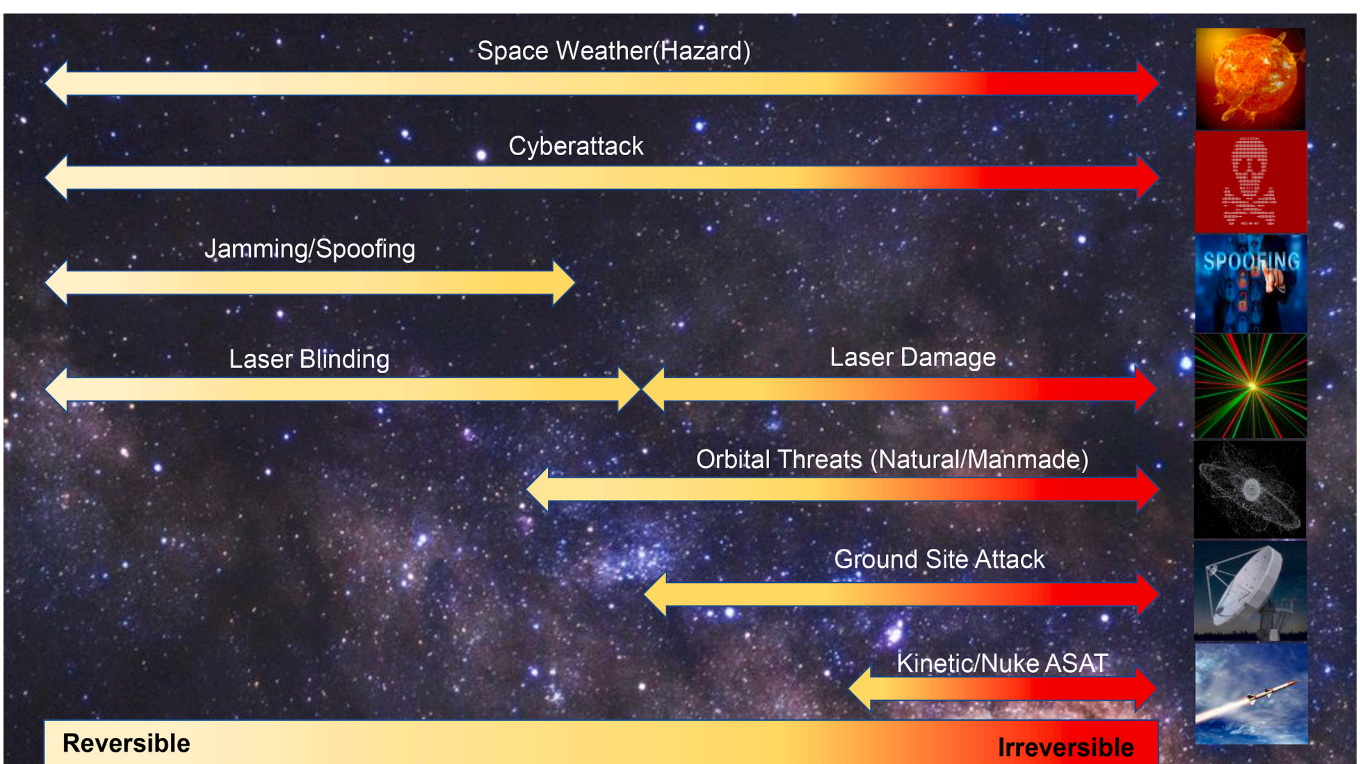

Fig. 28. Outer space threats. Adapted from Ref. [306].

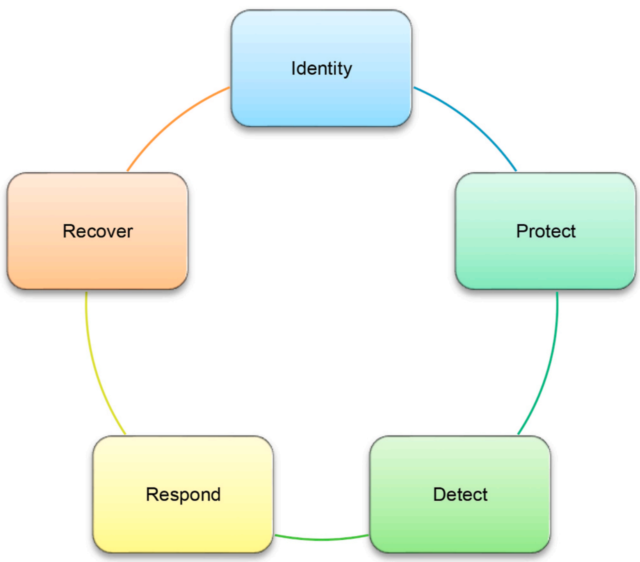

Fig. 29. Cybersecurity framework [275].

developed by The Aerospace Corporation (Fig. 30) looks at a system's capacity to fulfil mission objectives throughout the course of its full lifecycle. Once the mission's requirements and specific functions have been determined, the possible threats that can affect the mission should be identified, along with potential strategies. The threat's goals must be also identified because the strategy is a tool for attaining them [322]. Several AI approaches should be examined, along with their possibilities for practical adoption in the iDSS considering human supervision, with the aim of achieving TASO.

7.3. Safety considerations

Dependence on AI systems is critical for technological frameworks to be widely applicable and accepted. Standards, norms, accreditations and certificates are examples of legal regulations commonly used to formalise societal tools for expressing reliance [323]. Freed et al. [324] offer a Verification and Validation (V&V) methodology for autonomous space systems that aims to increase trust in the stability of complicated software. This approach combines runtime analyses and model control using software design architectures to enable traceable modular verification activities and automated code generation while delivering automatic formal V&V. Freed's intelligent automation system guarantees that software is conceived, produced and verified by domain experts-engineers and scientists for space activities, which is another important part of creating confidence in autonomous software [324]. Generally, the V&V system engineering approach is used for space mission development. In order to verify and validate the system, it must undergo a certain certification process based on their criticality level. Table 11 shows the critical levels of these ML models.

Well-established certification processes for traditional deterministic software applications cannot be applied in a straightforward manner in the context of ML, therefore major certification topics must be reconsidered. A comprehensive certification approach for ML applications would help to improve the overall quality and safe use of this technology, which would in turn increase public acceptance and trust. Winter et al. [323] proposed a certification standard for supervised learning with low-risk potential, illustrated in Fig. 31.

8. Technical, ethical and legal challenges

A wide range of opportunities exists for the application of AI to space systems. As discussed, AI can play a key role in achieving TASO (especially in DSS), although a number of technical and legal challenges arise with the adoption of these techniques, both during the development and operational phases of a space system's lifecycle [325–331].

8.1. Technical challenges

The iDSS concept introduces strict requirement on AI for trusted autonomy. The space vehicle and its components must be able to react quickly, adapt to changing situations and coordinate their operation with a potentially large number of other spacecrafts. A number of AI techniques are presently available to suit these needs, but several of them need further development and verification to attain full technological maturity and operational reliability. For instance, on-board AI is allowing shared mission planning operations between the control segment and the satellites. To implement sophisticate forms of data mining on the telemetry and other sensor data, several low-level commands must be aggregated as a single event. The human operator should take on the role of supervisor, which requires a transition away from the centralized command and control paradigm of legacy space systems and an increasing adoption of AI reasoning. A critical challenge in this process is the transition from deterministic to nondeterministic engineering design, but if distributed missions are the future, this evolution must be acknowledged and embraced. Of course, evolving the paradigm from the present rigid and inflexible safety assurance process to a more responsive and probabilistic approach would take time and developing a roadmap to make this process practicable will be one of the key milestones to advance in this direction [279]. Although several experts are concerned about the vulnerability or failure of AI algorithms on-board spacecraft, research has shown that they are critical for attaining mission goals in cybersecurity and satellite health monitoring. Despite the progress made, some difficult difficulties remain, requiring scientific breakthroughs. To date, the majority of progress has been accomplished in what is known as "narrow AI," which involves developing ML algorithms to fulfil specific and well-defined functions, such as natural language processing. More difficult problems are left to be dealt with by "artificial general intelligence," in which sophisticated AI approaches are developed to reason and solve problems in the same way that humans can. Despite the introduction of new approaches to address them, AI still faces a number of practical obstacles. The labelling of the training data required for supervised learning frequently necessitates a significant amount of human labour. Data sets that are large and thorough enough to train a model are likewise challenging to come by. The "explainability" difficulty arises from the intricacy of deep learning techniques' "black box" nature, although some success was achieved with post-hoc explanation methods revealing what factors contribute to a judgement or prediction and in what manner. Another obstacle is developing generalized learning strategies, as AI methods continue to have difficulty transmitting their experiences from one set to the next. A promising approach to addressing this challenge is transfer learning, in which an AI model is trained on a given task and then applied to a similar but separate activity [327]. One of the most significant technical challenges is data security; as ML training relies on large amounts of classified data, which is frequently sensitive and of a personal nature. As a result, it is subject to data theft and identity theft [332]. Another critical difficulty is data scarcity, as the accuracy and relevance of the supervised and labelled datasets used for training and learning directly affect the ML application's power and capabilities. Unfortunately, labelled datasets are scarce, so attempts are underway to develop approaches for making ML models learn despite the paucity of high-quality labelled data using transfer learning, active learning, DL and unsupervised learning [333]. Because several of these AI methods are based on training datasets, bias is a very significant issue. The correctness of AI decision-making capacity is determined by how well data was trained utilising real and unbiased facts. When data used for training is laced with racial, gender, community, or ethnic biases, unethical and unfair effects are inherently present. As many AI systems continue to be trained

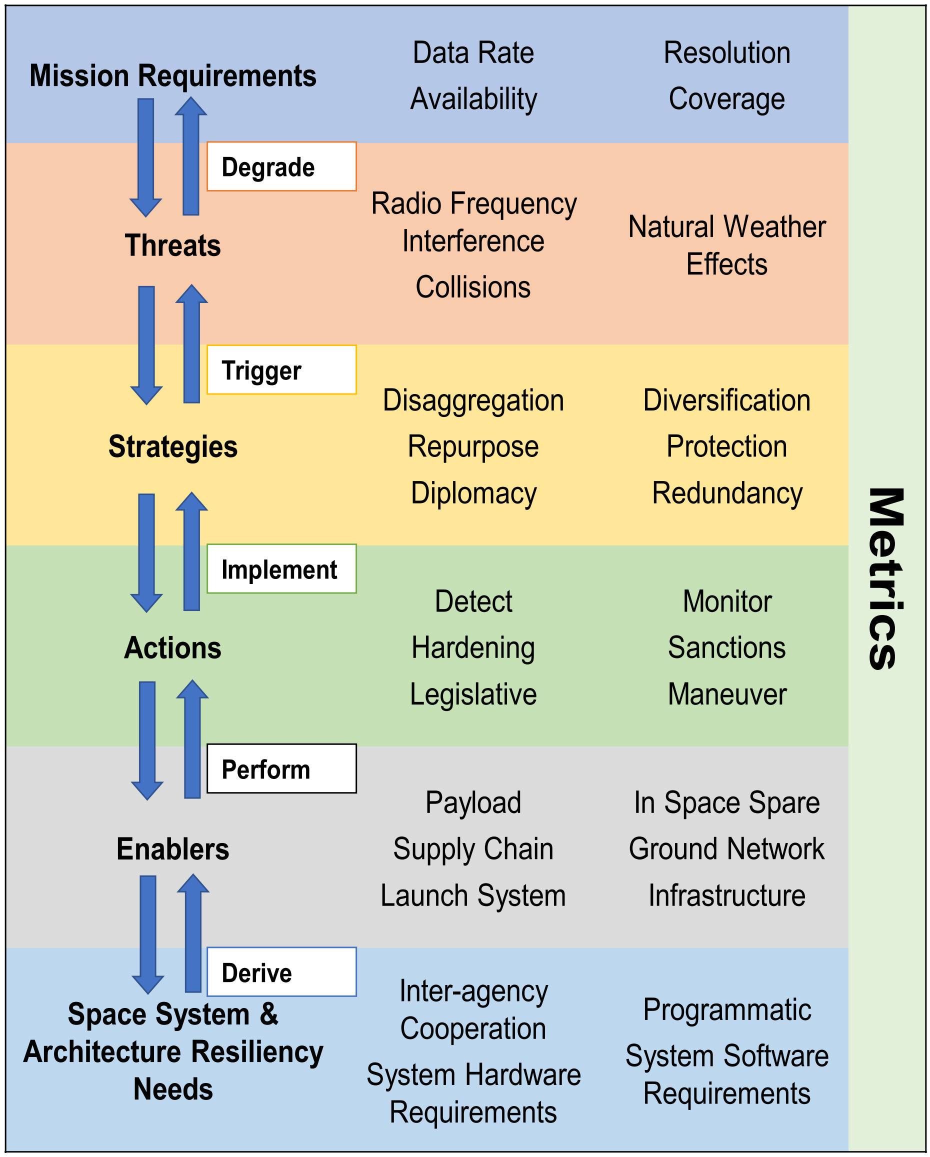

Fig. 30. Overview of the resiliency taxonomy [321].

with limited data, such biases are expected to become increasingly severe [326,334–336]. Table 12 lists the some of the foreseeable technological challenges associated to different application areas.

As of now, AI in space is limited to offline data processing and has not been adopted "on the edge" within the spacecraft [264]. When looking particularly at the most promising AI algorithms for spaceborne applications, several challenges are identified:

1. There are several reasons for this, including the difficulty of porting DL networks to hardware that predates the algorithms themselves and has insufficient performance to make even basic inferences. Many AI models and particularly DL require a large number of operations per second to meet the stringent real-time operational requirements of many on-board applications, making their inference computationally intensive [337].
2. In addition, quantization and pruning techniques can compress the model [338], potentially improving its accuracy over the original [339]. Different hardware can be exploited depending on the arithmetic representation used.
3. By performing model compression, network selection and design strategies can be used to mitigate memory budget problems. Certain neural network models, according to research, can be compacted without significant accuracy loss [340].
4. Another reason that may have slowed AI adoption for on-board applications is a lack of trust due to the inherent unpredictability. This nondeterminism arises from the impossibility of de facto testing the weights set due to training for all possible inputs using a finite amount of data. More predictable AI approaches are generally preferred because the high cost of failure is a critical factor in space applications [341].
5. AI applications could be limited to the payload level to reduce risks in EO missions, where object detection and classification could be performed locally on sensor data [342]. In this particular instance, AI failures would only affect the quality of data for a single payload rather than putting the satellite at risk [264].
6. The final point to consider is Deep Neural Network (DNN) training. Indeed, a significant issue is the lack of datasets for training and model evaluation, particularly for missions involving new equipment, such as novel sensors, for which no DNN training dataset exists. DNN training will also be performed on-ground, utilising cloud-based Graphics Processing Units (GPU) or more specialised training hardware such as Tensor Processing Unit (TPU) due to its

Table 11
ML criticality levels for certification [323].

Criticality Level (CL)	Impact Potential (Examples)	ML Application Requirements
1	There is no risk of harm to living beings, no risk of loss of confidential data and no ethical or privacy concerns.	Basic minimum requirements of a competently developed ML application are fulfilled.
2	Living beings could be harmed with limited, no permanent damage. Temporarily unavailability of non-critical data and services, violation of ethical concerns without identifiable harm to actual persons.	The ML application is developed according to industry standards and follows best practices that are regarded as state of the art.
3	Living beings could die or be restricted for life; the environment could be damaged. Manipulation of data with severe financial consequences and loss of control of the system to malicious attackers.	The ML application is developed and documented with great care. Safety & Security is ensured with processes and techniques that go beyond traditional best practices and industry standards.
4	Many living beings could die or could be restricted for life; the environment could be damaged permanently. Loss of information which endangers the existence of the organization. Long-term unavailability of critical data or services without which the organization cannot function.	The ML application is developed and documented with great care. Safety & Security is ensured with processes and techniques that go beyond traditional best practices and industry standards. All components of the ML application are formally secured and validated.

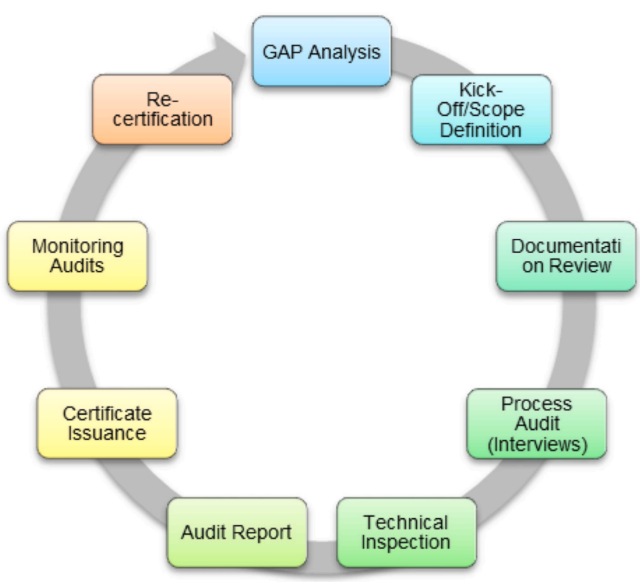

Fig. 31. Ml certification Workflow [323].

complexity. These factors raise serious concerns about the usability of models developed before the launch of satellites and not based on the original satellite data. However, this problem is mitigated by the ability to reconfigure models during the life of missions, which is enabled by the use of modern Commercial, Off-the-Shelf (COTS) and the smaller file sizes required for programming, which is becoming compatible with the uplink bandwidth of small satellites [264].

8.2. Ethical and legal challenges

The use of AI in space systems raises a number of ethical and legal questions. Some researchers have identified the need for AI ethicists to help navigate where advances in this technology could lead [328]. This is more exciting because AI and space technologies offer a wide range of opportunities. Nevertheless, the need to understand the ultimate outcome of the technology remains unanswered. Not to mention that even the scientific research community are unable to agree on a precedent arising from the use of AI. Prominent scientists and industry leaders argued that AI could radically transform the way we live and work, potentially threating our civilisation and even human survival [343]. A report on robotics and AI published by the British House of Commons highlighted specific ethical and legal issues, including transparent decision-making, minimising bias, accountability and privacy [325]. The first draft of the “Ethics Guidelines for Trustworthy AI” was published by the European Commission’s High-Level Expert Group on Artificial Intelligence (‘AI HLEG’) [344]. According to the guidelines, trustworthy AI must adhere to the following principles:

Table 12
Technological challenges for space systems in the upcoming decades. Adapted from Ref. [74].

Areas	Goals	AI Opportunities and Challenges
Sensing & perception	To provide situational awareness for autonomous space agents, explorers and assistants	•Algorithms for 3D perception, state estimation and data fusion •On-board data processing •Object, event or activity recognition
Mobility	To reach and operate at sites of scientific interest on extra-terrestrial surfaces or free space environments	•Multi-environment and multi-modal locomotion (e. g., flying, walking, climbing, rappelling, tunnelling, swimming, sailing) •Intelligent manipulation systems performing intentional changes to the environment (e.g., placing, assembling, digging, trenching, drilling, sampling, grappling and berthing).
High-level autonomy for system and sub-systems	To provide robust and safe autonomous navigation, rendezvous and docking capabilities and enable extended-duration operations without human interventions	•High-integrity GNC algorithms •Intelligent docking and capture algorithms •Autonomous mission planning, scheduling and control • Multi-agent coordination and cooperative control • Automated data analytics for autonomous decision making
Human-machine interactions	To enable humans to understand the machine’s state accurately and rapidly in collaboration and act effectively and efficiently towards the goal state	• Multi-modal interaction (virtual and augmented reality) • Remote and supervisory control • Distributed collaboration and coordination • Adaptive human-machine Interfaces • Cognitive human-autonomy interactions
System engineering	To provide a framework for understanding and coordinating the complex interactions of space CPS and to achieve the desired mission requirements	• DDT&E lifecycle evolutions • Verification and validation of complex/adaptive AI based systems • Digital threads and digital twins • Safety certification, trust and cyber-security

1. Ethical purpose: AI development, deployment and use should respect fundamental rights and applicable regulations as well as core principles and values to ensure "ethical purpose";
2. Technical robustness: AI should be technically robust and reliable since its use can cause unintentional harm, even in the presence of good intentions [344].

AI systems use large amounts of data, causing increasing concerns as more data is collected and used. Such high volumes and the level of dependence on such data will keep privacy at the forefront as one of the most significant legal issues to be addressed in the future. For instance, setting ethical parameters within which AI systems operate is paramount in tackling bias, considering the application of AI to data generated in space and prospective on-board AI space sector developments.

Another important issue is liability in closed-loop human-machine systems: if AI is used in a Decision Support Tool (DST) and an accident takes place, the critical question being raised is who is responsible, the operator or the designer of the AI-based DST? Based on the current legal framework, if the human operator did not follow the DST recommendation and the DST was right, s/he will be blamed for having made the wrong decision. If the operator, conversely, followed the DST and the DST was wrong, s/he will be blamed for having made the wrong decision. This is an obvious paradox, which will have to be properly addressed. Since we are dealing with complex CPH systems employing AI (i.e., interconnected and closed-loop human-machine systems), there is general consensus that the liability issues must be addressed primarily at the design and certification stage. This is because AI explainability and trusted autonomy are design attributes of such systems and not measurable/observable parameters during operations. Clearly, this is a major paradigm shift and requires radical changes in the current Design, Development, Test and Evaluation (DDT&E) industrial practices as well as the development (and uptake) of new operational standards and regulations. The tort of negligence, which is a common legal principle applied to liability, is concerned with whether a party owed another a duty of care, whether that duty was breached and whether the breach resulted in damages. In the case of negligence, reasonable foreseeability is a crucial concept [345]. As AI systems become less reliant on traditional algorithms, they will be able to exhibit behaviours that are not only unexpected by their creators and possibly unpredictable. In a scenario where there is a lack of predictability, the law could replace its negligence-based approach with one based a more holistic liability concept, which clearly specifies the allocation of responsibility to both AI/DST designers and operators. If, on the other hand, a negligence-based approach is retained, it will be necessary to define the applicable duty of care requirements in a hybrid AI-human operational context. Whichever the approach adopted, the regulation of AI will inevitably continue to pose significant challenges, which are exacerbated by the inherent continuous evolution of AI algorithms/applications and the associated need to develop a more flexible and responsive legal framework to keep pace with these technologies [344,345]. There are currently two main approaches to address lawmaking for AI [329]. The first approach stipulates that one must solve problems only as they arise (i.e., responsive in nature). There is no need to introduce new regulation when there is no problem. The main rationale behind this approach is that early (normative) intervention can prevent or even block certain innovation paths. The second approach is proactive and based on the premises that universal pre-emptive standards are necessary, without waiting for actual problems to occur. Whichever approach is pursued, it is important to note that the Outer Space Treaty requires international monitoring of the application of the rules and the establishment of an international law enforcement agency to carry out such monitoring [346]. Differences in national legal frameworks and in the uptake of international regulations/standards may challenge this process [347].

9. Conclusion and future research

Large and heterogeneous satellite constellations are becoming viable and advantageous options, eliciting an evolution of operational paradigms towards higher levels of autonomation and trusted autonomy. Despite the fact that achieving full autonomy is still a relatively distant goal, the demand for Artificial Intelligence (AI) is on the rise, creating new opportunities for expanded space system capabilities. While increasingly higher levels of automation have been introduced in conventional satellite systems, AI-based trusted autonomy is becoming essential in large Distributed Space Systems (DSS). Intelligent DSS (iDSS) are thus an evolving paradigm, which relies on new reactive and predictive functionalities, essential to accomplish Trusted Autonomous Satellite Operations (TASO). The adoption of safe, efficient and reliable AI techniques in all DSS segments unleashes unique opportunities to enhance the overall space mission lifecycle, and particularly the design, development and operational phases. To support the transition to TASO, a new dedicated AI design, verification and certification framework has to be established, addressing both autonomous cyber-physical systems and closed-loop human-machine system architectures. The certification of truly intelligent and evolving space systems is a critical undertaking and several aspects will have to be properly addressed to ensure the safety and security of these systems, including: (1) integrity of both system and data being exchanged; (2) consistency and resilience against adversarial threats; and (3) interpretability of the autonomous decisions.

Based on our review, it is evident that to safely integrate AI into all aspects of space operations, further research is needed in several areas. First of all, AI-based functionalities are needed for: (1) Mission Planning and Scheduling (MPS); (2) on-board data collection and processing; (3) reconfigurable networking for optimized data exchange with other space assets and ground terminals; and (4) autonomous detection, tracking and avoidance of orbital collision hazards. All these functionalities will require efficient and intelligent data analytics, interpretation and decision-making on-board satellites, both to minimize the data throughput requirements and to maximise mission responsiveness. Ideally, the associated AI techniques should have the ability to continuously enhance the iDSS performance through learning and adaptation. In terms of on-board Mission Planning and Scheduling (MPS), the AI techniques shall consider operational uncertainties and constraints, to optimise objectives, resource allocation and trajectory planning/replanning. In relation to this, research in autonomous detection and avoidance of collision hazards has to explore the effectiveness of incorporating AI models into the Space Based Space Surveillance (SBSS) for Space Domain Awareness (SDA). Particular emphasis should be given to algorithms that can improve the performance of tracking debris and other objects. This will, in turn, support the co-evolution of air and space traffic management (e.g., launch and re-entry provisions and point-to-point suborbital operations). Concerning the resilience of AI-based Cyber-Physical Systems (CPS) in space, the challenge is to develop robust, fault-tolerant and secure systems that ensure TASO given the specific hardware constraints, the variability of mission requirements, the uncertainties in physical processes and the possibility of both cyber/physical attacks and human errors. In particular, the development of Intelligent Health and Mission Management (IHMM) functions on-board space assets, which exploit AI to provide predictive integrity which can track the state of health and operational efficiency of space systems, detect anomalies and implement timely reconfiguration actions which minimize outages and risks of catastrophic failures. These functions form part of the autonomous mission MPS capability. To achieve the full potential of iDSS for Earth observation and astronomy, further research is needed into efficient AI algorithms capable of analysing and interpreting large volumes of mission data in real-time, prompting human review only when and where needed, therefore reducing the time and resources necessary in these missions. Another important aspect concerns the ethics and trustworthiness of AI-based CPS. In this respect, research should investigate the legal consequences of AI applications in the space sector and identify practical ways to ensure that AI-based decision-making systems are transparent, fair and accountable by design. Explainability and interpretability will be critical aspects of this endeavour and shall be explored in relation to the duality of human-autonomy interactions (i.e., integrity monitoring and augmentation of both human and autonomous agents). Once the robustness, fault-tolerance, security and ethical aspects are properly addressed, a comprehensive AI regulatory framework should be established to support the necessary evolution of systems engineering and lifecycle management practices (i.e., design, integration, test, certification and operations), which are still based on purely deterministic and relatively inflexible paradigms.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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